# The Choice between Arm's-Length and Relationship Debt: Evidence from eLoans*

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**Abstract**

Using a unique sample of comparable online and in-person loan transactions, we study the determinants of arm's-length and inside lending focusing on the differential information content across debt types. We find that soft private information primarily underlies relationship lending whereas hard public information drives arm's-length debt. The bank's relative reliance on public or private information in lending decisions then determines trade-offs between the availability and pricing of credit across loan types. Consistent with economic theory, relationship debt leads to informational capture and higher interest rates but is more readily available whereas the opposite holds true for transactional debt. In their choice of loan type, lender switching, and default behavior firms, however, anticipate the inside bank's strategic use of information and act accordingly.

# 1 Introduction

Banks typically offer two very different types of credit to their corporate customers: relationship loans characterized by inside information and transactional loans for which banks compete on a much more equal informational footing (see, e.g., Broecker, 1990, Rajan, 1992, Inderst and Müller, 2006, or Hauswald and Marquez, 2006). While the theoretical implications of competition between informed and uninformed lenders are well understood much of the empirical work has focused on relationship lending, in part because data on lending relationships is more readily available (see, e.g., Petersen and Rajan, 1994, Berger and Udell, 1995, or Elsas, 2005). Furthermore, private transactional debt with the attributes posited by the theoretical literature is hard to identify in practice. However, recent advances in lending technologies finally make available new data on credit-market transactions that closely fit the theoretical definition of transactional lending: online loans. Hence, we propose to fill this gap in the literature by analyzing the comparative determinants of online (transactional) and in-person (relationship) credit transactions.

Using a unique sample of all online and in-person loan applications by small businesses to a large US bank over a 15-months period we investigate a firm's choice between transactional ("arm's-length") and relationship ("inside") debt and the ensuing bank-borrower interaction to better understand the economic forces that shape exchange in these two market segments. For each loan application we collect the bank's ultimate credit decision and loan terms, its internal credit score, and the eventual loan performance. Although our bank's lending standards are identical across the two modes of origination loan officers can individually adjust internal credit scores for in-person applications that therefore contain a soft, subjective credit-assessment component supplied by branch offices. No such interaction or adjustment takes place for online applications. From credit-bureau reports we also know each applicant's Experian Small Business Intelliscore (XSBI) as a measure of publicly available information and can identify firms that refuse the offered terms to switch lenders.

The primary difference between arm's-length and relationship debt stems from each loan type's information content that determines the availability and pricing of credit. Hence, we first orthogonalize each applicant's bank-internal score with the publicly available XSBI score to obtain its private-information residual (PIR) as a clean measure of the lender's proprietary intelligence gathered in the screening process. We then follow the typical steps of bank-borrower interaction and estimate discrete-choice models of the firm's choice of lending channel, the bank's decision to offer credit and the borrower's to accept the loan terms, and linear-regression models of the offered loan's all-in cost. We round off our investigation of the differential information content of arm's length and relationship debt by studying the borrower's decision to switch lenders and the likelihood of credit delinquency across loan types.

The explanatory variables are proxies for public (Experian score: XBSI), proprietary (lender's internal score), and private information (orthogonalization: PIR), and the nature of the lending relationship or absence thereof. We control for borrower characteristics, loan terms, regional and business-cycle effects, and the prevailing interest-rate environment. Since the choice between transactional and relationship debt might depend on the local availability of credit we also include the number of lenders and their branches in each applicant's zip code to take into account competitiveness effects and, similarly, the firm's distance to bank's branch or online-processing center and to the nearest full-service competitor as proxies for transaction costs terms of time and effort.

We find that public and private information plays very different roles across lending channels because the bank predominantly relies on one type of intelligence for a particular debt product. Public information drives transactional credit decisions and pricing whereas private information collected through prior business interaction and the loan-origination process determines relationship-debt offers and their terms. We also show that the differential information content across debt types shapes the predicted trade-off between the availability and pricing of credit for each lending channel (Broecker, 1990, Rajan 1992, and Hauswald and Marquez, 2006). Arm's-length debt is less readily available but at lower rates because symmetrically informed banks, which compete on the basis of public information, not only drive down its price but also restrict access to credit to minimize adverse selection *ceteris paribus*. By contrast, better informed inside lenders strategically use their information advantage to informationally capture relationship borrowers that pay higher rates but gain easier access to credit.

Our results also reveal that firms anticipate the lender's strategic use of information and rely on their public credit score as a credit-quality indicator for their own best response. As a consequence, public information retains some measure of importance even in inside lending and influences firm decisions in both arm's-length and inside transactions whereas the bank's private information primarily matters to relationship borrowers. Given that firms take into account the inside bank's rent-seeking behavior but nevertheless engage in relationship transactions this finding strongly suggests that borrowers also benefit from close ties to their lender, for instance through better access to credit or intertemporal insurance effects.

The impact and statistical significance of our relationship variables confirm these effects across specifications and lending channels. Since online applications do not permit banks to generate much inside knowledge our lender discounts whatever private information might transpire in transactional lending. By contrast, lending relationships not only offer the opportunity to collect such intelligence but the length and depth of the interaction together with the firm's physical proximity are also good indicators of the information's quality (see, e.g., Agarwal and Hauswald, 2006 or Mian, 2006). The presence of established business relationships unsurprisingly enhances the effect of private information on inside lending but has a much smaller and often insignificant effect on arm's-length transactions.

Our main contribution consists in carefully identifying, measuring, and analyzing the differential information content of transactional and relationship debt on the basis of a large sample of credit transactions in a unified framework. Given the chosen mode of bank-borrower interaction we establish that the extent to which informational considerations shape the choice of debt product critically depends on the bank's ability to generate private information and benefit from it. An additional contribution consists in showing that borrowers also learn about their bank's policies and, in particular, its strategic use of private intelligence that determines the differential response of firms to banks' information-acquisition and lending strategies across debt types. Finally, our results highlight how technological progress in the form of online banking and credit scoring allows intermediaries to simultaneously engage in transactional and relationship lending, thereby helping them to overcome organizational limitations that in the past led to specialization by market segment or bank size (Berger *et al.,* 2005).

To the best of our knowledge, there is no comparative work on the differential effects of private and public information by loan type. While Petersen and Rajan (1994), Berger and Udell (1995), Degryse and Van Cayseele (2000), Elsas (2005), and Schenone (2007) have analyzed the importance of relationship banking for the collection of inside information they do not consider the respective use of public and private credit-quality signals across lending modes, which is central to our analysis. An exception are Bharath et al. (2006) who also find that information asymmetries induce borrowers to self-select into lending relationships but who do not consider transactional lending. Focusing on the benefits of relationship lending to borrowers Boot and Thakor (2000) argue that the resulting close business ties allow banks to fend off competition from other lenders and transactional debt, which is consistent with our data. Boot (2000) and Boot and Schmeits (2005) offer excellent surveys of recent theoretical and empirical work on relationship banking.

The paper also contributes to the nascent literature on the effect of the internet on financial intermediation. Wilhelm (1999, 2001), who analyzes the impact of the internet on the structure of banking markets and, especially, relationship banking, argues that technological advances change the collection and use of (private) information through its codification which is at the heart of our analysis. Similarly, Petersen (2004) discusses how technology affects the nature of the bank-borrower interaction and, hence, the operations of financial markets and institutions. Anand and Galetovic (2006) offer empirical predictions on the internet's effect on firm-bank relationships in terms of a shift toward non-relationship modes of interaction, which is only partly borne out by our results. Bonaccorsi di Patti *et al.* (2004) investigate demand complementarities between traditional and online provision of banking services and report that e-banking leads to a reduction in per-customer profitability which mirrors our findings on the competitive pricing of transactional debt. Regarding the importance of online banking Fuentes *et al.* (2006) study the determinants of the decision of U.S. banks to create a transactional website for their customers while DeYoung (2005) investigates the scale economies present in internet banking.

The paper is organized as follows. In the next section we review the theoretical literature on transactional and relationship debt and distill pertinent empirical predictions. Section 3 describes our data and estimation strategy. In Sections 4 and 5, we analyze the firm's choice of arm's-length vs. inside debt and the bank's decision to offer credit and at what price across lending channels. Section 6 investigates the determinants of the borrower's decision to reject the banks' loan offer and obtain credit from a competitor. In Section 7 we report our findings on credit default across loan types. The last section discusses further implications and concludes. We relegate all tables to the Appendix.

## 2 Transactional and Relationship Lending

The theoretical literature has typically argued that relationship lending offers particular economic benefits to at least one party, if not both, through the closer ties that banks and borrowers forge. Lending relationships allow intermediaries to gain proprietary information (Rajan, 1992 and Petersen and Rajan, 1994), facilitate renegotiation through the implicit nature of the debt contract (e.g., Sharpe, 1990), give rise to intertemporal transfers (e.g., Petersen and Rajan, 1995), and allow borrowers to learn about their bank's attributes (Iyer and Puri, 2007).[1] In fact, the ability to gather proprietary information (Bhattacharya and Chiesa, 1995) and use it strategically in credit-market competition has become the defining attribute of relationship debt. By contrast, lenders compete on a more equal informational footing for transactional loans, competing away potential rents but at the price of less readily available credit (Broecker, 1990 or Hauswald and Marquez, 2003). Hence, firms face a trade-off between the availability and pricing of credit across the two lending modes: informational capture with rent extraction but more flexibility in financing choices or less readily available credit at lower rates.

Relationship banking allows lenders to strategically acquire proprietary information and to create a threat of adverse selection for their rivals, thereby softening price competition. For instance, Petersen and Rajan (2002) argue that local banks who collect "soft" proprietary information on small firms over time have an informational advantage over more remote competitors who might not enjoy the same degree of access to local information.[2] Several empirical predictions follow. Given a firm's credit quality relationship lending facilitates the access to credit and intertemporal insurance but at the cost of rent extraction. Hence, the more and better proprietary information a bank has, the more willing it should be to approve loan applications but also the higher the quoted interest rate will be conditional on the applicant's credit quality (see, e.g., von Thadden, 2004). By contrast, symmetrically informed transactional lenders should charge less and be less willing to grant credit to applicants of comparable credit quality (see, e.g., Broecker, 1990).

By the same token, competition affects each lending channel differently. In purely transactional credit markets symmetrically informed lenders bid less aggressively because more competition wors-

[1] For a recent survey on relationship banking see Boot (2000).

[2] Mian (2006) or Agarwal and Hauswald (2006) provide strong evidence for this conjecture. See also Berger, Frame and Miller (2005) on the role of soft information in lending decisions and the ability of smaller banks that presumably have a more local focus to collect and process such intelligence.

ens their inference problem so that credit becomes less available and interest rates rise (Broecker, 1990). By contrast, when relationship and transactional lending directly compete with each other, e.g., a better informed inside bank against less informed arm's-length lenders, competition reduces the incentives for information acquisition so that interest rates should fall in both segments and credit availability rises because less informed transactional lenders face a diminished threat of adverse selection (Hauswald and Marquez, 2006).

A subtle difference in the adverse-selection problem that lenders face for each loan type is also behind the respective empirical predictions for borrower switching. In purely transactional credit markets, banks face symmetric adverse-selection threats so that *ceteris paribus* they can compete more aggressively for transactional borrowers who should be more likely to switch. However, when transactional lenders compete against a better informed inside bank, the greater the latter's informational advantage, the greater the threat of adverse selection. As a result, less informed competitors bid less aggressively (higher interest rates and less frequently) so that relationship borrowers are less likely to switch providers of credit. Hence, we expect less borrower switching in relationship lending, the greater the informational advantage of the inside bank is, or the less competitive a local credit market is. At the same time, better credit risks, which are the primary targets for rent extraction, should actively respond to such attempts by seeking loans elsewhere so that publicly observable signals of higher credit quality should induce more lender switching even by inside borrowers.

Finally, the more private information a lenders has the less likely errors in granting credit should become. Hence, a bank should experience less credit delinquency in relationship than in arm's-length lending. Also, the greater the competition the greater (smaller) adverse-selection problems become in transactional (relationship) lending so that competition should increase the incidence of default in transactional loan markets and decrease it in relationship debt.

From an empirical perspective, the defining features of transactional and relationship debt then revolve around the generation and strategic use of proprietary information, differential availability and pricing of credit, and the resulting competitive reaction as revealed by lender switching across loan types. While the length and scope of a prior business relationship is thought to reveal the existence of a lending relationship no such clear-cut identifier has existed for transactional debt in the past. However, the advent of online lending to small businesses without any personal interaction between the parties allows us to unambiguously identify purely transactional loans. At the same time, lenders often engage in extensive information acquisition through their branch offices so that in-person applications and the resulting interaction with local loan officers define relationship debt.

# 3 Data Description and Methodology

Our sample consists of all online and in-person applications for new loans over a 15-months span by small firms and sole proprietorships to a large US financial institution with a particular regional focus on New England, the Mid-Atlantic, and Florida. During the sample period, this lender ranked among the top five commercial banks and savings institutions according to the FDIC. Since our bank more or less automatically rolls over prior loans on request unless a significant deterioration in creditworthiness has occurred very different considerations drive the decision to grant credit from the one renewing an existing loan. As a result, most information production takes place around the origination of a new loan, explaining our sample selection. All loan applications fall under the definition of small- and medium-sized enterprise lending in the Basel I Accord so that the total obligation of the applying firm is less than $1 million and its sales are below $10 million.

We focus on small-business lending because borrowers exhibit just the right degree of informational opacity for our purposes and credit products in this market are typically close substitutes. On the one hand, firms are sufficiently opaque for proprietary information to matter in lending decisions. On the other hand, small businesses are also quite homogeneous so that bank competition is intense, several lending channels coexist, and third parties provide credit-scoring services that we can use to measure the contribution of our bank's own proprietary loan screening to credit decisions.[3]

## 3.1 Operational Policies

The small-business loans originate both from personal visits to branch networks and from websites without any personal interaction so that we can clearly identify whether credit is granted on an arm's-length or relationship basis. In case of an in-person application, the firm's representative

[3]Since our data provider applies a uniform credit-scoring methodology to all loan requests the internal credit score is a consistent and meaningful measure of the bank's proprietary information across applicants, branches, and distribution channels.

(e.g., owner/manager) personally visits one of the 1,408 branch offices in our sample (out of a total of 1,552)[4] to supply all the relevant information, submit financial statements and tax data, provide a list of assets, etc. The local loan officer transcribes this information into electronic form and matches it with credit reports for input into the bank's proprietary credit-scoring model. The whole lending process including the credit decision typically takes four hours to a day from the initial meeting between applicant and loan officer.

The loan officer also uses the branch visit to conduct an in-depth interview with the applicant to gather "soft" information in the sense that it would be hard to verify by a third party. In up to 8% of the cases, the branch will invite the applicant back to follow up on open questions, review discrepancies in submitted information with credit reports, discuss the prospects of the firm, etc. Such information allows the branch manager or account officer to subjectively adjust the firm's internal score should the applicant deserve credit in their eyes but fail to meet certain commercial, profitability, liquidity, or credit-score requirements. These subjective score revisions represent the soft-information component of the bank's internal credit assessment that forms the basis of our analysis.

Each branch office enjoys a considerable amount of autonomy in the assessment, approval, and pricing of loans but has to justify any deviation from bank-wide practices. As a consequence, credit decisions ultimately reside with branches because local managers can alter credit scores on the basis of a standard set of subjective criteria that the final score reflects. Similarly, they can adapt loan terms including pricing to the specific circumstances of the application. However, branch managers' career prospects and remuneration depend on the overall success of their credit decisions, and local "overrides" are closely monitored by the bank's overall risk management.

In case of online applications, the applicant submits all the requisite information through a website. The online processing center then requests credit reports to cross-check the information and computes the firm's credit score very much like a branch office but does not attempt to resolve any informational discrepancies. As a matter of operational policy, there is no personal interaction between the bank and an online applicant so that our lender makes online-credit decision purely based on its internal credit score, which is not subject to any revisions and computed on the basis of

[4]For comparability, the 100 institutions with more than $10 billion in assets in 2002 operated, on average, 364 branch offices. Their average amount of deposits is about a quarter of our data provider's deposit base.

firm-supplied information, credit reports, and, possibly, prior interaction. Similarly, any loan terms, especially interest rates, are solely a function of the firm's credit score, its ability to post collateral, third-party guarantees, etc. As a result, both credit offers and their terms are highly automated in the online market, closely corresponding to the definition of transactional debt because the lender does not gather additional intelligence beyond publicly available information.

Most monitoring is automated for both loan types and takes place through the daily tracking of current-account movements or balances[5] (whenever available) and prompt debt service. On a monthly basis, the bank collects new credit reports for the firm and its owner and updates the account's risk profile. Yearly credit reviews and the treatment of overdue loans, however, differentiate ongoing information production across lending channels. On each anniversary of the loan's origination, transactional borrowers submit updated financial information online. Relationship borrowers have to do so in-person at their branch office, which uses the visit to discuss the firm's prospects, state of solvency, funding needs, etc. Similarly, if a payment is between 10 and 20 days late on a relationship loan the account officer will personally visit the firm. If the account becomes more than 20 days overdue, the bank cuts back credit lines to the current balance, i.e., reduces its credit commitment, but will not take such action on term loans before 60 days past-due.

Although the lending standards are identical across online and in-branch origination the resulting transactions differ in their information content because loan officers and branch managers can personally revise applicants' credit scores on the basis of subjective impressions. At the same time, the two lending channels effectively compete within the bank because branches have no incentive to encourage in-person applicants to also apply online. As a result, the observed loan type allows us to cleanly sort credit applications into transactional or relationship debt with the required informational attributes.

## 3.2 Data Description

The sample consists of all applications for new loans to our bank that conform to the Basel I Accord's SME lending definition between January 2002 to April 2003 (36,723 observations). We match these records with credit-bureau reports (Experian and Dunn & Bradstreet) on the application

[5] Mester *et al.* (2007) find that current-account transactions provide valuable information for loan monitoring in a setting similar to ours.

date to verify the supplied information and delete applications with missing data (e.g., Experian credit score) or other informational discrepancies such as nonexisting addresses. Our data provider also engaged in several M&A transactions affecting its branch network so that we also omit all re-assigned loan records. Overall, we lose 2,868 credit requests leaving a total of 7,945 online applications and 25,910 in-person ones. Table 1 summarizes our data as a function of the applicant's chosen form of interaction with the bank and reports the $P$-values of $t$-tests for the each variable's mean conditional on the lending channel.[6]

To analyze informational effects in transactional and relationship lending we rely on the outcome of the bank's own borrower assessment in terms of the internal credit score calculated for each loan application. While the methodology is proprietary and subject to confidentiality restrictions, the credit-screening procedure is consistent across all branches, lending channels, and applications because it uses a common set of inputs and the same statistical model. For in-person applications, our bank's credit scores comprise a subjective element because local branches provide "soft information" through individual adjustments that can over-ride automated lending decision and centralized loan pricing. From periodic surveys of loan officers the data provider estimates that 20% to 30% of the in-person score ultimately consists of subjective (soft) information. We use the final scores whose revisions follow bank-wide guidelines and require detailed justification by branches. Internal scores for online applications are not subject to revision and therefore comprise at most hard, i.e., independently verifiable, proprietary information.

Internal scores range from 0 (worst) to 1,850 (best). Their means (medians) are 899 (902) for online applicants and 930 (949) for in-person ones, and the difference is significant at the 1% level ($P$-value of 0.00%). We also collect the applicant's Experian Small Business Intelliscores (XSBI), which this leading credit bureau provides together with its report services, as a publicly available signal for each firm's creditworthiness. We reverse the Experian scores, which measure the likelihood of "serious delinquency" over the next 12 months, and linearly rescale them for comparability with the better known (retail) FICO scores so that the XSBI variable ranges from 300 (worst) to 850 (best). Contrary to the internal score, the average (median) of online applicants' Experian scores is statistically significantly higher: 723 (704) against 716 (705) for in-person applicants ($P$-value

[6]For confidentiality reasons, the data provider did not allow us to report further descriptive statistics because they could be used to "reverse-engineer" the composition of the loan portfolio.

of 0.00%).[7] This discrepancy in scores across loan types stems from the subjective revisions to internal credit assessments for in-person applicants. It highlights not only the informational value of relationship lending but also shows how banks incorporate subjective information such as personal impressions of borrower quality into credit decisions.

We assess the nature of the lending relationship, which facilitates the collection of such borrower-specific information, along two dimensions.[8] Our first variable is the number of months that a particular firm has been on the books of the bank, which measures the length of the lending relationship. We see that in our sample online applicants have, on average, obtained a first credit product 27.7 months prior to the loan application whereas in-person applicants have been borrowers for 30.8 months. The second variable measures the breadth of the business relationship. To this end we define a binary variable Scope in terms of the balance of the firm's current account (at least $5,000) together with prior borrowing and the purchase of at least one other banking product (Scope: about 20% of online against 30% of in-person applications).

To control for the availability of public information and firm-specific attributes we rely on the months a particular applicant has been in business (64 vs. 103 months for online and in-person applications, respectively), which is a good proxy for informational transparency, and the firm's monthly net income ($64,734 vs. $101,109 for online and in-person applications, respectively) that captures size and profitability effects. We also use 38 industry dummy variables based on the applicants' two-digit SIC codes to account for any industry effects in the data. Table 1 shows that our sample represents a wide cross-section of industries, albeit with a particular emphasis on wholesale and retail trade, personal, business and professional services, and construction. Similarly, we rely on state and quarter dummy variables to account for regional and business-cycle effects.

To measure the competitiveness of local credit markets we collected the number of bank branches and active lenders in a firm's zip code from the FDIC's Summary of Deposits data base by year. Concentration measures such as the Herfindahl-Hirschman Index of deposits or branch shares by firm ZIP code are not statistically significant in our specifications so that we do not tabulate their sample statistics or estimation results.

[7] The US mean (median) for comparable consumer FICO scores is currently 678 (723). See Experian (2000, 2006) for further details on the SBI and its ability to forecast credit delinquency.

[8] James (1987), Lummer and McConnell (1989), and Elsas (2005) present evidence suggesting that banks gain access to private information over the course of the lending relationship.

In terms of loan characteristics our data contains the requested loan amount (mean of $37,333 and $46,877 for online and in-person applications, respectively, in line with typical small business lending), its maturity (mean: 5.43 and 6.74 years, respectively), and existence of collateral (about 42% for online against 55% for in-person applications). About 17% (37%) of online (in-person) credit requests were personally guaranteed by guarantors with a monthly income of $23,745 ($35,164). 19.6% (28%) of online (in-person) applications are for term loans, the remainder is for credit lines. As a matter of business policy, our bank only offers term loans at fixed rates and credit lines at variable rates so that our Term Loan (vs. credit line) binary variable also captures the nature of the interest rate. Finally, 3.74% of online against 6.41% of in-person applications fall under the terms of the Small-Business Administration (SBA) guarantee program.

To control for the ease and cost of personally transacting with the bank in terms of time and effort we use the driving distance in miles between each firm and their branch office for in-person applications or, for consistency, the processing center for online request, as well as the distance to the closest full-service branch of a competitor.[9] We see that relationship borrowers are on average located 10.3 (median: 2.8) miles away from their bank branch whereas transactional applicants are 91.7 (median: 31.9) miles away from the bank's online-loan processing center. By contrast, both transactional and relationship applicants are about 1 mile on average (median: 0.5 miles) from the nearest full-service branch of a competing lender.

Since banks and their customers might choose to locate in certain areas based on local economic conditions, we include the Case-Shiller Home Price Index (CSHPI: see Case and Shiller, 1987, 1989) to account for potential endogeneities in the parties' choice of location and lending channel. By matching each loan application with the index by zip code and month we also capture loan-transaction effects that are due to the local level of economic activity, differences in affluence across postal zones, and differential levels of urbanization or road infrastructure as reflected in local house prices.

We see that, contrary to common perceptions, transactional applicants are typically younger and

[9] See Degryse and Ongena (2005) on the importance of transportation costs in credit markets. We rely on Yahoo!SmartView and Yahoo!Maps to identify the nearest competitor for all loan applicants and to determine the driving distances between the firm, the bank branch for personal applications or the processing center for online ones, and the competitor's branch. SmartView has the dual advantage that it does not accept sponsored links and draws on the combined yellow-page directories of BellSouth and InfoUSA (Mara, 2004) providing objective and comprehensive bank-branch information.

smaller firms that request smaller loan amounts, offer less collateral and personal guarantees, and are more creditworthy according to publicly available information (XSBI). However, they are less likely to have a prior business relationship with the bank and, if so, it is shorter than for in-person applications. As a result, the bank's internal score as a proprietary measure of credit quality is higher for relationship borrowers, presumably through subjective revisions that incorporate private local information into the credit decision.

### 3.3 Methodology

Our estimation strategy simply retraces the steps of the loan-origination process starting with a discrete-choice model of the firm's choice of loan type as a function of publicly available and proprietary information, characteristics of the lending relationship, firm attributes, and our control variables. We next investigate the bank's credit decision by estimating a logistic model of its decision to offer credit by lending channel and, if so, at what price. To this end we specify a linear model of the offered annual-percentage rate (APR: the all-in cost of credit taking into account fees and commissions) as a function of the same variables once again taking into account the debt type.

Successful loan applicants typically move next by accepting or declining loan offers. Hence, we explore the differential effect of private and public information across debt type on bank competition as revealed by an applicant's decision to switch lenders. Lastly, the respective informational and competitive dynamics of each lending mode hold different implications for type II errors in credit screens and, hence, default across loan types. We therefore estimate the likelihood of borrower delinquency by lending channel to assess the incidence of debt type on the quality of the bank's public and private information in terms of loan performance.

For every decision in the lending process, we specify logistic discrete-choice models with separate equations for each lending channel so that we can compare informational effects across debt types and directly test empirical predictions in a unified econometric framework. For instance, we estimate the likelihood of a loan offer $Y_i = 1$ as

$$E\left[Y_i \left| \mathbf{x}_i \right.\right] = E\left[\left(1 - 1_{eloan}\right) Y_i + 1_{eloan} Y_i \left| \mathbf{x}_i \right.\right] = \Pr\left\{Y_i = 1 \left| \mathbf{x}_i \right.\right\} = \Lambda\left(\mathbf{x}_i' \boldsymbol{\beta} + 1_{eloan} \cdot \mathbf{x}_i' \boldsymbol{\gamma}\right) \qquad (1)$$

where $\Lambda\left(\mathbf{x}_i'\boldsymbol{\beta}\right) = \frac{\exp\left\{\mathbf{x}_i'\boldsymbol{\beta}\right\}}{1+\exp\left\{\mathbf{x}_i'\boldsymbol{\beta}\right\}}$ is the logistic distribution function. The binary variable $1_{eloan}$, which takes the value 1 for online applications and 0 otherwise, allows us to report results by debt type because we have

$$E\left[\hat{Y}_i \,|\mathbf{x}_i\right] = \Lambda\left(\mathbf{x}_i'\hat{\boldsymbol{\beta}}+1_{eloan}\cdot\mathbf{x}_i'\hat{\boldsymbol{\gamma}}\right) = \begin{cases} \Lambda\left(\mathbf{x}_i'\left(\hat{\boldsymbol{\beta}}+\hat{\boldsymbol{\gamma}}\right)\right) & \text{for transactional debt } (1_{eloan}=1) \\ \Lambda\left(\mathbf{x}_i'\hat{\boldsymbol{\beta}}\right) & \text{for relationship debt } (1_{eloan}=0) \end{cases}$$

Similarly, we specify the following linear-regression model of the offered loan's all-in cost (APR) $r_i$:

$$r_i = \mathbf{x}_i'\boldsymbol{\beta}+1_{eloan}\cdot\mathbf{x}_i'\boldsymbol{\gamma}+\varepsilon_i \tag{2}$$

We focus on the following key variables in our investigation of the differential information production in transactional and relationship lending: each firm's Experian Small Business Intelliscore ($XSBI$) as a measure of publicly available information, its internal credit score as a measure of the lender's proprietary information, the scope and months-on-book variables measuring the depth of the lending relationship, and a measure of soft private information. To extract this purely private component of credit screens we orthogonalize the internal and Experian scores because the former relies on a mix of public and private intelligence as inputs into the proprietary scoring model. Specifically, we estimate the bank's private credit assessment as the residual $\hat{u}_i$ of the regression

$$\ln\left(IntScore_i\right) = \beta_0+\beta_1\cdot XSBI_i + 1_{eloan}\left(\gamma_0+\gamma_1\cdot XSBI_i\right)+u_i \tag{3}$$

which we label the Private-Information Residual (PIR). Incidentally, the $R^2$ of the above regression are 0.67 and 0.71 for the online and in-person equations, respectively, which confirms our data provider's contention that up to 30% of the internal score is based on soft, subjective information.[10]

The Private-Information Residual $\hat{u}_i$ represents a clean measure of our data provider's soft private information whenever it exists. Given its construction, the online PIR captures hard private intelligence only to the degree that it exists for eLoans through repeat business, verification of self-reported information with credit reports, and the lender's proprietary scoring methodology. In addition to such hard private information, the in-person PIR also comprises a soft subjective component stemming from the loan officer's personal impressions of borrower quality incorporated

[10] For confidentiality reasons we cannot provide further details on the orthogonalization nor report any results. The log-linear specification best agrees with the nonlinear nature of Experian's Small Business Intelliscore.

into the internal score through the interview, follow-up, and revision process. Since we compare the PIR across two equations in the same specification the transactional eLoans become the *de facto* benchmark which we use to measure the additional and, hence, soft information content of in-person credit applications. Note, however, that we can also interpret the residual $\hat{u}_i$ as a proxy for the bank's informational advantage over publicly available information regardless of debt type.

To control for systematic effects in self-selection and approval practices across branches and lending channels we estimate all our specifications including the internal-score orthogonalization with branch fixed effects and rely on clustered standard errors that are adjusted for heteroskedasticity across bank branches and autocorrelation within offices including the online-loan processing center. The estimation of all discrete-choice models proceeds by full-information maximum likelihood; we report their pseudo $R^2$ which is simply McFadden's likelihood ratio index whenever appropriate.

It is worthwhile to point out that the unique nature of our data set allows us to sidestep pervasive endogeneity problems that arise in the study of the credit terms when the sample only consists of booked loans (see, e.g., Berger *et al.*, 2005). Since our data comprise all applications and loan offers potential borrowers have not chosen yet whether to accept or to refuse the lender's terms. The omission of declined loan offers could give rise to the joint endogeneity of borrower characteristics, bank attributes, and loan terms, which we avoid through sample selection by including the 1,335 ultimately declined offers in this part of the analysis. Since several of the variables fit better in logarithms than levels we use the former whenever appropriate.

## 4 The Choice between Arm's-Length and Relationship Debt

Specification 1 in Table 2 reveals that public credit-quality perception is by far the most important criterion in a firm's choice of loan type. Applicants, who presumably have a good sense of their own creditworthiness, are the more likely to choose arm's-length debt the higher their public credit score is: a 10% increase in the firm's Experian score raises the likelihood of applying online by 2.15%. The second important determinant is Months on Books. The longer a firm has been a borrower at our lender the more likely it is to apply in-person for a relationship loan. We also see that, contrary to widespread perceptions, the firm's size, profitability, age, and ability to post collateral do not seem to enter into the applicant's choice of loan type: Net Income, Months in Business, and Collateral are all statistically insignificant.

However, lending relationships allow information to flow in both directions so that borrowers typically learn about their bank's operational policies, too (e.g., Iyer and Puri, 2007). Furthermore, verbal communication between the loan officer and firm representative during the origination interview often reveals bank-internal information to applicants who use such knowledge in their own decision making. Hence, we would expect the lender's proprietary and private information as measured by the Internal Score and PIR to be correlated with borrower perceptions of bank-internal credit assessments. To capture this facet of lending relationships we successively add these two variables to the specification. We see that the inclusion of the Internal Score dramatically reduces the marginal effect of the public score lending support to our contention that the former can also serve as a proxy for borrower impressions of their bank's credit-quality signal, which increases their likelihood of applying online (Specification 2, Table 2). However, in terms of economic significance the marginal effect of public information, i.e., the XSBI score, is almost four times that of the Internal Score.

To the extent that loan officers communicate their subjective impressions not only to their own institution (through score revisions) but also to customers (during the interview), applicants might also become aware of the bank's private information. Hence, we next replace the Internal Score with its orthogonalization in terms of the XSBI, the Private-Information Residual (PIR). Comparing Specifications 2 and 3 in Table 2 we see that the distinction between proprietary (Internal Score) and private (PIR) information is crucial. Only when we properly measure the latter as the former's orthogonal complement to public information do we find the predicted sign pattern so that public signals of high credit quality are associated with transactional debt and private signals with relationship lending. To preclude any possibility of spurious correlation between the PIR and dependent variable arising from our two-equation estimation (3) we reestimate the specification with the residuals from a pooled orthogonalization but do not report the results because they are virtually identical.

The two overriding factors for the firm's choice of debt type are now the public credit-quality signal, whose marginal effect is almost unchanged from the previous estimation, and our private-information measure PIR ( Specification 3, Table 2). Not only are their marginal effects of comparable magnitude but their opposite signs also conform to perceived notions of the differential information content present in transactional and relationship lending. A better public credit-quality signal makes the firm more likely to apply online for a transactional loan because applicants that are presumably aware of their own credit risk know that a higher public score improves their access to (cheaper) arm's-length debt and act accordingly.

Conversely, a firm with a longstanding banking relationship might be able to infer its lenders's credit-quality assessment if only because of the signalling value of repeated loan offers. It can count on being well regarded and, hence, on preferential treatment by its bankers, who, in turn, gain better access to inside information. As a result, we would expect the firm's application loan-type decision and the bank's private credit-quality signal to be correlated. The PIR's large negative marginal effect in Specification 3 of Table 2 bears out this conjecture. The better the private credit-quality assessment, the less likely the firm will request a transactional loan and instead apply for relationship credit in-person at a branch office. Since the PIR also measures the inside bank's informational advantage vis-à-vis competitors this finding suggest that despite the danger of informational capture better private information actually increases a firm's likelihood of choosing relationship debt through the promise of future benefits such preferential access to credit or intertemporal transfers.

To further investigate this hypothesis we next add interaction terms between the PIR and relationship variables to capture the potential for collecting private information and the borrower's awareness of such efforts (Specification 4, Table 2). Both the PIR-Months-on-Books and PIR-Scope effects further support our interpretation that despite the danger of informational capture borrowers well known to their bank seek relationship debt precisely because loan officers can better communicate their (high) opinion of good credit risks to those customers during negotiations. The longer (Months on Books) or broader (Scope) the parties' interaction the more likely the firm will choose relationship debt and the more important the existence of private information becomes for this choice of loan type.

The fact that both the lender's informational advantage and prior borrowing strongly increase the probability of a relationship-loan request provides additional support for our conjecture that firms not only are aware of their lender's information but also benefit from special ties to their bank. Firms know that longstanding business relationships facilitate the access to credit precisely because loan officers tend to have a better picture of their prospects. Exposed to the danger of informational capture by their bank, applicants of high perceived credit quality might as well benefit from more readily available credit that inside debt typically offers in such circumstances, a topic that we turn next to.

# 5 Credit Decision by Lending Channel

In this section, we analyze the availability and pricing of credit by origination mode to determine the differential information content of arm's-length and relationship debt. Table 3 reports summary statistics for the key variables by credit decision and lending channel, in particular loan terms and pricing. Two facts consistent with the theoretical predictions on debt type stand out: rejection rates are much higher for online applications (about 61% as compared to 49% for in-person requests), and credit spreads are on average much lower for transactional than for relationship loans (279 and 453 basis points, respectively). Credit appears to be much less readily available through transactional channels but, when it is, loan rates are much more favorable.

## 5.1 Credit Availability

The results for the bank's decision to grant credit show that transactional debt is much harder to obtain than relationship debt *ceteris paribus.* Both specifications in Table 4 reveal that applying online lowers the probability of a loan offer by up to 11.2%. Transactional lenders know that they compete on a much more level informational playing field in this segment, if not at an outright disadvantage should the firm also be seeking inside credit elsewhere. To avoid potential adverse-selection problems they have to be much more circumspect in their arm's-length lending and refrain from offering credit more often, thereby lowering the probability of an online loan offer (see, e.g., Broecker, 1990 or von Thadden, 2004).

Specification 1 in Table 4 shows that the likelihood of obtaining transactional credit increases in both the public and proprietary credit-quality signal (XSBI and Internal Score, respectively): the better the outcome of the credit screen, be it public or bank-internal, the easier access to online loans becomes. However, an increase in the Internal Score has only a small, albeit statistically highly significant, impact on the likelihood of obtaining transactional credit. By contrast, the Experian score (XBSI) is not statistically significant in the relationship-loan equation. Instead, positive proprietary credit assessments containing a mixture of soft private and hard public information primarily decide the access to inside credit. This finding suggests that not only the origin of the bank's information but also how it processes and interprets its intelligence matters for relationship lending.

To carefully distinguish private from public information we again replace the Internal Score with its Private-Information Residual (PIR) and add the relationship-PIR interaction terms to the model (Specification 2 in Table 4). Our results confirm that different types of information shape each credit-market segment. Although both the PIR and Experian score are statistically significant in each equation, the relative magnitudes of the variable's marginal effects are reversed across loan types. Transactional-credit decisions primarily rely on public information (XSBI score) whereas private information (PIR) only has a small impact; in fact, the marginal effect of a positive public credit signal is almost 8 times larger than that of a positive private credit-assessment. By contrast, private information is the overriding factor in the decision to offer relationship credit because its marginal effect is almost five times larger than the small positive impact of public information.

Comparing the relative impact of public and private information on credit availability across loan types we see that the marginal effect of positive private information is 15 times greater for relationship than for transactional lending. Interestingly, the importance of a high public credit score does not differ as much across the two lending modes (only 5.5 times lower) and retains its statistical significance at 5% in the relationship-loan equation (Specification 2). In light of the fact that lenders and loan types compete with each other this finding is less surprising than it might otherwise be. The theoretical literature has long argued that good credit risks are the primary targets for informational capture in relationship lending (e.g., von Thadden, 2004) and, therefore, more likely to switch providers of credit. Hence, banks know that public perceptions of credit quality matter in the competitive response of other lenders that try to poach borrowers. As a result, the Experian score not only captures credit-quality effects but also acts as a proxy for the expected intensity of competition for the borrower.

We conclude from both specifications in Table 4 that, consistent with theoretical predictions, private information primarily determines access to inside debt whereas public information drives arm's-length lending. Banks specifically gather more costly private information for borrowers that through their chosen mode of interaction with the lender facilitate its collection and signal their willingness to be informationally captured. The differential impact of the length and scope of the banking relationship across loan types confirms this interpretation. Scope and Months on Books are statistically insignificant in the decision to offer arm's-length credit but highly significant both in statistical and marginal terms for relationship-loan offers. Taken together these effects suggest that a prior lending relationship enhances the likelihood of obtaining inside credit precisely because they facilitate the collection and interpretation of (private) information. By contrast, prior interaction is less relevant for the decision to grant transactional loans because there is no opportunity to revise online applicants' scores in light of additional information.

Similarly, we see that the firm-bank distance is only statistically significant (at around 5%) in the in-person-loan equation. The closer a potential relationship borrower is to a branch office the higher the likelihood of obtaining credit becomes. In addition to capturing physical transaction costs, the bank-borrower distance is an excellent proxy for the quality of the lender's private information and, hence, informational advantage (see Agarwal and Hauswald, 2006). Petersen and Rajan (2002) argue that soft subjective information, whose collection borrower proximity and prior lending relationships facilitate, is crucial for lending decision. No such opportunity to collect soft information and incorporate it into credit decisions exists in the case of transactional loans, which might explain the statistical insignificance of the relevant variables in the eLoan equation.

A comparison of the two specifications in Table 4 shows that all the other effects remain virtually unaffected by the inclusion of the Private-Information Residual. The firm's size or profitability (Net Income) and its ability to post collateral or to guarantee the loan raises the likelihood of a loan offer for each lending channel and the marginal effects are very comparable. The local-competitiveness effects closely correspond to theoretical predictions. More competition, i.e., a higher number of competing lenders or branches in the firm's zip code, decreases the likelihood of obtaining a loan of either type because competition decreases the average quality of the applicant pool (see, e.g., Broecker, 1990) so that banks refrain more often from offering credit.

Our findings suggest that the use and, hence, quality of proprietary intelligence radically differs across lending channels. The limited ability to gather inside information or, equivalently, its high cost in transactional lending forces banks to discount any private knowledge and instead to rely on publicly available signals of credit quality. As a result, banks compete on a much more equal informational footing, which borrowers recognize and incorporate into their choice of loan product. By contrast, banks heavily rely on private information gathered through inside lending in relationship-credit decisions. Although lenders can use their informational advantage to soften competition through the threat of adverse selection and to extract information rents it also facilitates relationship borrowers' access to credit (see, e.g., Hauswald and Marquez, 2006). By the same token, our credit-decision results validate the firm's perception of the importance of personal interaction and private information for obtaining relationship loans discussed in Section 4.

### 5.2 Loan Pricing

To investigate differential credit pricing across lending channels we next estimate linear models of the loan's offered all-in cost (APR) as a function of our previously described explanatory variables. Like the internal score of in-person applicants, branches can adjust both the loan terms and pricing in light of local conditions and information. No such adjustment opportunity exists for eLoans whose price is a simple function of the internal score, the ability to post collateral or personally guarantee the loan, etc. Table 3 provides descriptive statistics for the offered loan terms by credit channel. To control for the interest-rate environment, we rely on the maturity-matched (interpolated) US Treasury yield on the loan date and the difference between the 5-year and 3-months US Treasury yield (Term Spread: yield-curve shape). We estimate the model with the Heckman correction for sample-selection bias (Lambda) to take into account the lender's prior credit decision.

Table 5 shows that arm's-length debt is up to 138 basis points less expensive than inside debt *ceteris paribus*. Specification 1 summarizes the effects of relationship variables, firm attributes, loan terms, and various controls on offered loan rates. Adding the informational variables (Specifications 2 and 3), we observe the same relative importance of public, proprietary, and private information in the determination of offered loan rates across lending channels that we found for the prior credit decision. Even with our measure of proprietary information Specification 2 in Table 5 shows that the impact of the public (XSBI) and internal score on the quoted all-in cost symmetrically varies across lending channels. An increase in the Experian score (XSBI) greatly reduces transactional loan rates whereas bank perceptions of higher credit quality (Internal Score) lead to a much more modest reduction in rates. The exact opposite is true for relationship loans whose price is much more affected by a rise in the Internal Score than in the XSBI one. These effects are all the more pronounced that the Experian score is highly nonlinear in implied credit quality.

Replacing the bank's credit score with the Private-Information Residual reinforces this conclusion (Specification 3, Table 5). Our measure of private credit assessments now becomes statistically insignificant in the eLoan equation but retains its high statistical significance in the in-person equation. The same is true for the relationship-PIR interaction variables that increase the private-information effect for relationship loans but are statistically insignificant in the transactional-loan equation. Any pure private information the bank can gather is mostly valuable in inside lending to limit competition and informationally capture relationship borrowers. Its poorer quality for online borrowers does not offer any significant benefits over publicly available creditworthiness signals. Hence, our bank disregards the purely private component of its credit assessments in the pricing of transactional debt which primarily results from symmetrically informed competition on the basis of public credit-quality signals. We also note that competition effects do not seem to significantly figure in the pricing of transactional or relationship loans.

Interestingly, the relationship variables Scope and Months on Books (statistically) significantly reduce not only the offered APR of relationship debt but also the cost of transactional debt. Contrary to the credit decision, the prior purchase of other products from the bank and the length of a lending relationship enters into the pricing of transactional loans. One possible explanation might revolve around rewarding customer loyalty in the presence of very low switching costs in online lending (see also Schenone, 2007). As a result, prior lending could be a significant factor in banks' pricing policy but less for informational considerations, which the bank addresses through the decision to grant credit, than to retain a customer of proven profitability. Adding the interaction terms in Specification 3 lends further credence to this interpretation. In the eLoan equation, the interaction terms are statistically insignificant whereas the relationship variables retain their significance. In the in–person equation the interaction terms are highly significant so that the relationship variables enhance the beneficial effect of a higher private credit-quality signal. Hence, prior business interaction affects inside-loan rates more by improving the quality of credit assessments so that banks place greater weight on their private information in the pricing of relationship debt.

It is also worthwhile to point out that a firm's age matters for the pricing of transactional but not relationship debt. Older, more established firms pay less for loans but the effect is statistically significant only for online offers. The opposite is true for firm profitability (Net Income) that only matters for the pricing of relationship debt. Again, informational effects might be at work. The longer a firm has been in existence the more publicly available information exists which is particularly valuable in the pricing of transactional debt. By contrast, financial data such as net income are self-reported in online-loan applications and, therefore, susceptible to manipulation. It is very costly to follow up on financial information for online applications so that our data provider seems to disregard it in this case. By contrast, loan officers can easily verify such information during the branch visit by in-person applicants (from, e.g., tax filings) and, hence, place more trust in financial statements.

The other explanatory variables have very similar effects across the two loan types. In particular, we note that the ability to post collateral or to personally guarantee a loan reduces loan rates by 210 to 239 and 30 to 81 basis points, respectively, depending on the lending channel. This finding contrasts with previous work such as Berger and Udell (1995) or Carey, Post, and Sharpe (1998) who report that collateral is associated with higher spreads. However, their results are probably due to the fact that collateral acts as a proxy for nonmeasured risk characteristics. Our finding that, once we explicitly control for borrower risk through the inclusion of various credit-quality measures (XSBI, internal score, PIR), collateral and guarantees reduce loan rates and, given our specification, credit spreads bears out this conjecture (see also Inderst and Müller, 2006). In fact, Booth and Booth (2006) also find that, controlling for the interdependence between the decision to pledge collateral and borrowing costs, secured loans typically carry lower spreads.

Taken together our results provide very strong empirical evidence for the predicted trade-off between the availability and pricing of credit across lending modes. In their choice of loan type, firms face a choice between easier access to relationship debt and lower priced transactional debt. Furthermore, we establish that different types of information lead to this trade off. The limited ability to gather proprietary intelligence in transactional lending forces banks to rely more on public information that further levels the playing field. Hence, online borrowing combines lower interest rates with a lower probability of receiving credit *ceteris paribus.* By contrast, the bank's ability to collect private information and to strategically use it enhances the likelihood that an in-person applicant receives credit albeit at the price of higher rates and informational capture, a topic we turn to next.

## 6 Lending Competition and Borrower Choice

By comparing credit offers to actually booked loans and matching the observations with credit-bureau information on competing loan offers we identify 420 transactional and 915 relationship borrowers that decline the bank's terms and seek credit from a competitor around the same time.[11] Table 6 provides summary statistics by debt type in function of the borrower's decision to accept or to decline the offer. We see that, on average, the declined loan offers are very similar to accepted ones for each lending channel.

When the degree of information asymmetry varies by borrower credit transactions become more contested as the informational advantage of the better informed lender falls. Less precise credit assessments decrease the threat of adverse selection so that less informed competitors can bid more aggressively by offering credit more often and at lower rates, thereby eroding the more informed bank's ability to earn information rents (see, e.g., Hauswald and Marquez, 2006). Hence, the smaller our bank's informational advantage becomes the more frequently borrowers should switch lenders. In the limit, when all banks are symmetrically informed, price competition dissipates any information rents and transactional borrowers frequently switch lenders. The implied switching rates in Table 6 bear out this prediction: transactional borrowers are almost twice as likely as relationship ones to decline a loan offer and seek credit elsewhere (13.39% against 6.98%).

To investigate differences in competitiveness across debt type we next estimate a logistic discrete-choice model of the successful loan applicant's decision to switch lenders. Specification 1 in Table 7 shows that, in line with theoretical predictions, transactional borrowers are almost 5% more likely to decline loan offers and seek credit elsewhere. As we conjectured earlier, the public credit-quality signal (XSBI) is by far the most important factor in inducing applicants to decline loan offers. The higher a firm's public score, the easier it becomes to switch lenders explaining the variable's high marginal effect even for inside borrowers whose decisions otherwise are more strongly correlated with private or proprietary information revealed to them over the course of the business relationship or origination process.

By contrast, private credit-quality signals (PIR), which act as proxies for the borrower's perception of the lender's private credit assessment, have a large marginal effect only in the in-person

[11] This decision is very different from borrower's choice of single vs. multiple banking relationships; see Detragiache *et al.* (2000) and Farinha and Santos (2002).

equation of Specification 2 in Table 7. Firms rationally anticipate that banks attempt to informationally capture inside borrowers and act accordingly so that the amount and quality of private information predicts switching behavior. The better the bank's own credit assessment of a relationship borrower, who can infer the existence of a positive private credit-quality signal from the offer alone, the more likely the latter is to switch lenders. As before, the firm's decision and the bank's private information should therefore be correlated, which explains why the Private-Information Residual has such a large impact on the switching behavior of relationship borrowers.

Curiously, the relationship variables (Scope, Months on Books) reduce the likelihood of declining a loan offer for both transactional and relationship borrowers. The large marginal effects and high statistical significance of the relationship-PIR interaction terms in the in–person equation suggest that informational effects are at work. The bank's desire to retain prior customers might explain a similar effect for transactional borrowers. Unsurprisingly, the higher the quoted loan rate the more likely are firms to decline the offer and seek credit elsewhere irrespective of the chosen loan type. Not only is it easier for better credit risks to obtain competing loan offers, they are also the primary targets for rent extraction through loan pricing and, hence, have a larger incentive to switch lenders. Consistent with theoretical predictions the effect is more pronounced for relationship borrowers that face a greater threat of informational capture.

We also see that competition matters but that the effects display an interesting pattern across loan products. For transactional borrowers, the likelihood of switching lenders increases in the number of locally competing institutions presumably because of name recognition, geographically targeted promotional campaigns, etc. By contrast, the switching behavior of relationship borrowers rises in the number of locally competing branch offices so that branch-proliferation effects and the easier access to personal interaction they offer matter.

Our results are broadly consistent with strategic lending by inside banks that use private information to informationally capture high-quality relationship borrowers.[12] The better the bank's information, i.e., the higher the quality of its credit screen or the closer a borrower is located to a branch, the easier it becomes to extract rents because our lender has a larger informational advantage over its competitors. Such attempts, however, fail in the transactional-loan segment

[12]See also Sharpe (1990), Rajan (1992), or von Thadden (2004) on this point. For evidence on the resulting winner's curse in banking see Shaffer (1998).

where symmetrically informed competitors can compete more aggressively for online borrowers. As a result, the public perception of credit quality drives a firm's decision to switch lenders all the more that borrowers are more likely than not aware of their own Experian scores, which is a good indicator for the likelihood of receiving a competing loan offer.

# 7 Information Production and Credit Delinquency

Our credit-bureau data also allow us to trace type I (denying a loan to a good credit risk) and type II (offering a loan to a bad credit risk) errors in credit decisions across loan types. Regarding the former, out of the 4,810 unsuccessful online applicants 3,321 firms (69%) managed to obtain a loan from another source within a month of their loan-application's rejection. By contrast, less than half (6,347 out of 12,808) in-person applicants were able to do so. Although transactional borrowers have a lower *ex ante* probability of obtaining a loan (see Tables 3 and 4) their cost of seeking credit online is lower, too so that they typically file more loan applications than relationship borrowers and, therefore, have a higher success probability *ex post*.

In terms of type II errors in screening, our sample contains 91 transactional loans (about 3.5%) and 319 relationship ones (2.7%) that have fallen 60 days past-due, which corresponds to our data provider's internal definition of a non-performing loan, within 18 months of origination.[13] We first note that the incidence of credit delinquency is significantly higher in the transactional subsample. To put the respective default rates into perspective, we also trace the credit delinquency of successful applicants that switched lenders. Their default rates are 4.5% and 5.8% for arm's-length and relationship loans, respectively, which is much worse than our bank's own loan performance. Default rates for unsuccessful applicants that were able to obtain a loan elsewhere are very high but do not vary much by lending channels: 24.79% and 24.63% for online and in-person (denied) applications, respectively. We interpret these default frequencies as evidence that our lender minimizes type II error in credit decisions by trying to avoid lending to bad credit risks. In doing so, the bank is more successful for relationship loans than transactional ones, for which intermediaries generally

[13] We choose this window so that the likelihood of a loan becoming overdue is still related to the initial credit assessment and not to subsequent economic events beyond the bank's control. Although the technical definition of default is 180 days past-due lenders typically take action after at most 60 days past-due either writing off the loan, selling it off, or assigning it for collection. As a result we do not know which of the delinquent loans ultimately experience default although over 90% of loans that are 60 days overdue eventually do according to our data provider.

suffer higher adverse-selection problems.

To investigate the differences in loan performance across transactional and relationship lending we estimate a logistic model of credit delinquency in terms of our usual information, relationship, and control variables by lending channel. Table 8 shows that transactional borrowers are up to 2.9% more likely to default than relationship ones *ceteris paribus*. The results also exhibit the usual pattern in information effects across equations. Public information (XSBI score) has by far the largest impact on the likelihood of default for both loan types. Positive private information (internal score, PIR) only affects the performance of relationship loans in an economically significant manner. Again, proprietary intelligence is primarily useful for mitigating credit risk in relationship lending but adds less to the bank's ability to predict the performance of transactional loans.

The marginal effects of the relationship variables that are much larger for in-person than online loans and, especially, the PIR-relationship interaction terms confirm this effect. Banks benefit from lending relationships through better private information that allows them to decrease their borrower-specific credit exposure. Similarly, the Months in Business variable has quite a large and statistically significant marginal effect on decreasing the risk of default across both lending modes presumably because there is more information - private or public - available for older firms. The loan amount has a large negative effect on the likelihood of default that is more or less constant across lending channels and specifications. In contrast to DeYoung *et al.* (2004) who report that the probability of default on small-business loans increases in the distance between borrower and lender we do not find any significant distance effects for either loan type.

The small but highly significant positive marginal effects of the competitiveness measures are consistent with theoretical predictions that more competition implies more adverse selection and, hence, more default. The informational effects, however, suggest that different forces are responsible for each lending channel. In transactional lending, more competition decreases the average quality of the borrower pool so that each lender suffers more adverse selection (Broecker, 1990). When competition increases for relationship borrowers, the informed lender has less of an incentive to acquire private information and the overall quality of its loan portfolio falls (see, e.g., Gehrig, 1998).

## 8 Conclusion

This paper presents an in-depth comparative analysis of the respective roles of private and public information in arm's-length and inside-debt transactions. The advent of online lending and banks' distinct operational practices across lending channels offer the opportunity to unambiguously identify transactional loans that match in all other respects traditional relationship debt. Using an exhaustive sample of online and in-person loan requests by small businesses we are able to determine the relative importance of private and public information for each debt type. At the same time, our data also allows us to investigate how the chosen form of bank-borrower interaction affects the lender's acquisition of private and proprietary information, its strategic use in credit decisions, and the borrowers' response for each form of debt.

Our results reveal that banks rely on different types of information for each lending mode. Public information primarily drives credit availability and pricing in transactional lending whereas private information determines credit decisions for relationship loans. Since banks have less opportunity to generate borrower-specific information from arm's-length debt they compete on a more symmetrically informed basis and rely more heavily on public information in their transactional credit decisions. The opposite is true for relationship loans. We find strong evidence that banks disregard publicly available information when they have access to better "soft" private information through inside lending that becomes the foundation of their relationship-credit decision and pricing.

By the same token, borrowers base their choice of debt type mainly on public credit-quality information that is readily available to them and provides them with a sense of their success chances in each credit-market segment. Furthermore, we find evidence that inside borrowers anticipate on the existence and consequences of private information. Longstanding business relationships imply more inside information together with preferential treatment so that the likelihood that a firm will seek a relationship loan increases in the lender's private credit-worthiness signal. Similarly, a firm's decision to decline relationship debt or to default on it depends more on the bank's private information than transactional debt although public information retains some importance for these choices, too. These findings are consistent with the notion that borrowers recognize the value of lending relationships for banks' ability to acquire proprietary information and to strategically use it.

However, the benefits of a lending relationship must ultimately outweigh the cost of informational capture for firms that otherwise would not selfselect into inside debt. Hence, our findings also provide support for the contention that relationship borrowers benefit from the closer ties with their banks. The fact that in-person loan applicants have, on average, a much longer and deeper relationship with their bank than online applicants lends additional credence to this interpretation. Such benefits typically revolve around intertemporal transfers between the parties, i.e., the notion that banks are more willing to finance borrowers that would otherwise not be able to find funding if they can recover the initial costs through future rent extraction or better loan performance. To directly investigate the existence of such benefits, however, one would need panel data on bank-borrower interaction over a longer time period. We leave this question for future research.

Table 1: **Descriptive Statistics for All Loan Applications**

| **Lending Channel** | **Online Application** | | | **In-Person Application** | | | ***t*-Test** |
|---|---|---|---|---|---|---|---|
| Variable | Mean | Median | Std Dev | Mean | Median | Std Dev | *P*-val |
| Loan Amount | $37,333 | $34,320 | $124,921 | $46,877 | $39,749 | $42,693 | 0.0000 |
| Maturity (years) | 5.43 | 5.18 | 2.05 | 6.74 | 6.20 | 5.34 | 0.0000 |
| Term Loan (vs. Credit-Line) | 19.57% | | 38.01% | 28.06% | | 46.86% | 0.0000 |
| Collateral | 41.54% | | 41.75% | 54.91% | | 48.64% | 0.0000 |
| Primary Guarantor | 17.09% | | 39.83% | 36.59% | | 47.59% | 0.0000 |
| Primary Guarantor's Monthly Salary | $23,745 | $20,821 | $107,148 | $35,164 | $32,012 | $88,582 | 0.0000 |
| SBA Guarantee | 3.74% | | 14.59% | 6.41% | | 15.90% | 0.0000 |
| Internal Credit Score | 899.22 | 902.05 | 73.40 | 930.51 | 949.38 | 133.29 | 0.0000 |
| Public (XSBI) Credit Score | 723.57 | 704.67 | 55.87 | 716.74 | 703.78 | 57.55 | 0.0000 |
| Private-Information Residual | 0.0059 | 0.0003 | 0.4975 | 0.0003 | 0.0005 | 0.6316 | 0.4676 |
| Scope of Banking Relationship | 19.92% | | 35.03% | 30.40% | | 43.66% | 0.0000 |
| Months on Books | 27.68 | 23.32 | 48.52 | 30.79 | 22.65 | 43.20 | 0.0000 |
| Monthly Deposit Account Balance | $12,649 | $10,835 | $16,040 | $14,363 | $11,014 | $41,669 | 0.0003 |
| Months in Business | 63.88 | 54.30 | 41.62 | 103.56 | 89.24 | 103.08 | 0.0000 |
| Firm's Monthly Net Income | $64,734 | $58,521 | $77,808 | $101,109 | $90,108 | $315,463 | 0.0000 |
| Case-Shiller House Price Index | 168.53 | 152.10 | 36.08 | 166.40 | 154.79 | 31.14 | 0.0000 |
| Firm-Bank Distance (miles by car) | 91.74 | 31.90 | 80.91 | 10.29 | 2.82 | 25.12 | 0.0000 |
| Firm-Comp Distance (miles by car) | 0.89 | 0.54 | 1.16 | 1.02 | 0.52 | 1.53 | 0.0000 |
| State CT | 8.32% | | 10.32% | 12.89% | | 35.04% | 0.0000 |
| State MA | 23.53% | | 41.26% | 15.18% | | 35.73% | 0.0000 |
| State ME | 2.32% | | 14.36% | 3.14% | | 17.28% | 0.0001 |
| State NH | 2.88% | | 16.34% | 2.58% | | 15.67% | 0.1500 |
| State NJ | 16.32% | | 34.85% | 24.53% | | 42.62% | 0.0000 |
| State NY | 35.53% | | 45.73% | 35.77% | | 47.61% | 0.6947 |
| State PA | 0.27% | | 5.08% | 3.08% | | 17.07% | 0.0000 |
| State RI | 4.86% | | 21.29% | 3.20% | | 17.46% | 0.0000 |
| Other States | 2.00% | | 1.76% | 0.17% | | 4.00% | 0.0000 |
| Q1 2002 | 17.02% | | 34.62% | 18.34% | | 38.43% | 0.0062 |
| Q2 2002 | 15.19% | | 36.00% | 18.61% | | 38.99% | 0.0000 |
| Q3 2002 | 17.45% | | 36.03% | 17.48% | | 37.70% | 0.9577 |
| Q4 2002 | 20.62% | | 37.80% | 19.01% | | 38.66% | 0.0011 |
| Q1 2003 | 23.99% | | 35.06% | 27.13% | | 32.96% | 0.0000 |
| SIC 0: Agriculture, Forestry, Fishing | 2.20% | | 14.49% | 3.02% | | 16.99% | 0.0001 |
| SIC 1: Mining, Construction | 9.93% | | 27.70% | 13.29% | | 33.62% | 0.0000 |
| SIC 2: Manufacturing (Consumer) | 2.80% | | 15.49% | 2.41% | | 15.20% | 0.0486 |
| SIC 3: Manufacturing (Industrials) | 3.38% | | 17.09% | 3.05% | | 17.02% | 0.1341 |
| SIC 4: Transport., Comm., Gas, Elect. | 4.26% | | 19.33% | 4.94% | | 21.66% | 0.0124 |
| SIC 5: Wholesale and Retail Trade | 25.94% | | 42.21% | 31.01% | | 45.78% | 0.0000 |
| SIC 6: Finance, Insurance, Real Estate | 4.48% | | 19.94% | 3.35% | | 17.64% | 0.0000 |
| SIC 7: Personal & Business Services | 19.68% | | 37.61% | 19.19% | | 39.10% | 0.3235 |
| SIC 8: Professional Services | 13.62% | | 31.33% | 13.21% | | 33.28% | 0.3264 |
| SIC 9: Administration | 0.30% | | 5.46% | 0.13% | | 3.51% | 0.0006 |
| Number of Branches | 4.51 | 2.77 | 4.53 | 4.78 | 3.00 | 5.36 | 0.0000 |
| Number of Institutions | 3.58 | 2.57 | 4.15 | 3.55 | 2.99 | 3.38 | 0.4629 |
| Number of Observations | | 7,945 | | | 25,910 | | 33,855 |

This table presents summary statistics for the variables described in Section 3 for our full sample of 33,855 data points in function of the firm's choice of lending channel. The last column indicates the *P*-values of a two-sided *t*-test for the equality of the variables' mean conditional on the loan's type (wherever appropriate).

Table 2: **The Choice of Lending Channel and Loan Type**

| **Specification** | **1** | | | **2** | | | **3** | | | **4** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Coeff | $P$-val | Marg | Coeff | $P$-val | Marg | Coeff | $P$-val | Marg | Coeff | $P$-val | Marg |
| Constant | -2.1933 | 0.0001 | | -2.0659 | 0.0001 | | -2.0708 | 0.0001 | | -2.0612 | 0.0001 | |
| ln(1+XSBI) | 0.5347 | 0.0001 | 21.46% | 0.4646 | 0.0001 | 14.15% | 0.4502 | 0.0001 | 14.18% | 0.4502 | 0.0001 | 14.30% |
| ln(1+Internal Score) | | | | 0.3582 | 0.0001 | 3.80% | | | | | | |
| Private-Info. Res. | | | | | | | -0.8958 | 0.0001 | -9.83% | -0.9009 | 0.0001 | -9.77% |
| Scope | -0.1345 | 0.7590 | -0.03% | -0.1202 | 0.5331 | -0.02% | -0.1201 | 0.7879 | -0.03% | -0.1194 | 0.7920 | -0.03% |
| ln(1+M. on Books) | -0.6809 | 0.0001 | -6.88% | -0.6896 | 0.0001 | -6.29% | -0.6959 | 0.0001 | -7.14% | -0.6796 | 0.0001 | -7.03% |
| Scope·PIR | | | | | | | | | | -0.3522 | 0.0346 | -2.58% |
| ln(1+MOB)·PIR | | | | | | | | | | -0.1014 | 0.1179 | -1.80% |
| ln(1+M. in Business) | 0.1193 | 0.9820 | 0.15% | 0.1048 | 0.8862 | 0.10% | 0.1104 | 0.9080 | 0.17% | 0.1096 | 0.9011 | 0.17% |
| ln(1+Net Income) | -0.0738 | 0.4932 | -0.98% | -0.0756 | 0.4871 | -1.01% | -0.0789 | 0.5000 | -1.00% | -0.0776 | 0.4987 | -0.98% |
| ln(1+CSHPI) | -0.1020 | 0.9223 | -0.78% | -0.1007 | 0.9210 | -0.71% | -0.1049 | 0.9270 | -0.81% | -0.1035 | 0.9860 | -0.81% |
| ln(1+F-B Dist) | 0.9874 | 0.0001 | 1.87% | 1.0053 | 0.0001 | 1.93% | 1.0121 | 0.0001 | 1.92% | 1.0183 | 0.0001 | 1.90% |
| ln(1+F-C Dist) | -0.2644 | 0.0001 | -1.04% | -0.2663 | 0.0001 | -0.95% | -0.2912 | 0.0001 | -1.05% | -0.2863 | 0.0001 | -1.05% |
| Collateral | -0.2148 | 0.6349 | -0.71% | -0.2162 | 0.6400 | -0.75% | -0.2356 | 0.6893 | -0.73% | -0.2311 | 0.6780 | -0.72% |
| Primary Guarantor | -0.0444 | 0.9320 | -0.01% | -0.0480 | 0.7368 | -0.01% | -0.0480 | 0.9110 | -0.01% | -0.0481 | 0.9170 | -0.01% |
| SBA Guarantee | -0.0791 | 0.0158 | -0.32% | -0.0766 | 0.0001 | -0.37% | -0.0842 | 0.0130 | -0.34% | -0.0834 | 0.0136 | -0.34% |
| Term Loan | -0.0769 | 0.9202 | -0.08% | -0.0818 | 0.9447 | -0.09% | -0.0823 | 0.9848 | -0.09% | -0.0821 | 0.9740 | -0.09% |
| ln(1+# Branches) | 0.1929 | 0.7745 | 0.03% | 0.2135 | 0.6971 | 0.03% | 0.2060 | 0.7760 | 0.03% | 0.2071 | 0.7760 | 0.03% |
| ln(1+# Competitors) | 0.1001 | 0.6338 | 0.02% | 0.1013 | 0.6329 | 0.02% | 0.1094 | 0.6377 | 0.02% | 0.1093 | 0.6351 | 0.02% |
| 4 Quarterly Dum. | | Yes | | | Yes | | | Yes | | | Yes | |
| 8 State Dummies | | Yes | | | Yes | | | Yes | | | Yes | |
| 38 SIC Dummies | | Yes | | | Yes | | | Yes | | | Yes | |
| Number of Obs | | 33,855 | | | 33,855 | | | 33,855 | | | 33,855 | |
| Pseudo $R^2$ | | 4.84% | | | 5.30% | | | 5.21% | | | 5.23% | |

This table reports the results from estimating a logistic discrete-choice model of the firm's choice of loan type by full-information maximum likelihood for our full sample (33,855 observations). The dependent variable is the firm's decision to apply online for a transactional loan ($Y = 1$: 7,945 observations) or in-person for a relationship loan ($Y = 0$: 25,910 observations). We estimate the specification $\Pr\{Y_i = 1\,|\mathbf{x}_i\} = \Lambda(\mathbf{x}_i'\boldsymbol{\beta}+1_{eloan}\cdot\mathbf{x}_i'\boldsymbol{\gamma})$, where $1_{eloan} = 1$ for online applications and 0 otherwise and $\Lambda$ is the logistic distribution function $\Lambda(\mathbf{x}_{ik}'\boldsymbol{\beta}_k) = \frac{\exp\{\mathbf{x}_{ik}'\boldsymbol{\beta}_k\}}{\sum_n \exp\{\mathbf{x}_{in}'\boldsymbol{\beta}_n\}}$, with branch fixed effects and compute clustered standard errors that are adjusted for heteroskedasticity across branch offices and correlation within.

The explanatory variables are our proxies for public (Experian's Small Business Intelliscore $XSBI$), proprietary (Internal Score) and private (Private-Information Residual) information, bank-borrower relationship characteristics (Scope, Months on Books abbreviated "MOB" in the interaction terms), firm attributes, the competitiveness of local credit markets (number of competing lenders and competing branches), proxies for the ease of transacting with lenders (firm-bank and firm-competitor distances abbreviated F-B and F-C Dist, respectively), and control variables for local economic conditions (Case-Shiller house-price index abbreviate CSHPI), the business cycle (quarterly dummies), state, and firm's industry (see Section 3 for a description of the variables).

The Private-Information Residual (abbreviated "PIR" in the interaction terms) measures the bank's pure private information that we obtain from orthogonalizing the internal and Experian scores. Specifically, the PIR for each observation is the residual $\hat{u}_i$ of the branch fixed-effects regression $\ln(IntScore_i) = \alpha_p + \beta_p \cdot XSBI_i + 1_{eloan}(\alpha_e + \beta_e \cdot XSBI_i) + u_i$.

We report the coefficients ( "Coeff"), their $P$-values ("$P$-val"), and marginal effects ("Marg") for the decision to apply online ($Y = 1$) but suppress the results for the business-cycle, state, and industry control variables in the interest of readability. Since the probabilities of applying online or in person sum to 1 the marginal effects for the choice of a relationship loan are simply the opposite of the reported ones. We obtain the marginal effects by simply evaluating $\frac{\partial \Pr}{\partial x_j} = \Lambda'(\mathbf{x}_i'\boldsymbol{\beta})\,\beta_j$ at the regressors' sample means and coefficient estimates $\hat{\boldsymbol{\beta}}$. The pseudo-$R^2$ is McFadden's likelihood ratio index $1 - \frac{\log L}{\log L_0}$.

Table 3: **Descriptive Statistics for the Credit Decision by Lending Channel**

**Panel A: Online Loan Applications**

| **Loan-Application Outcome** | **Accept** | | | **Reject** | | | ***t*-Test** |
|---|---|---|---|---|---|---|---|
| Variable | Mean | Median | Std Dev | Mean | Median | Std Dev | *P*-val |
| Loan Rate (APR: all-in cost of loan) | 6.91% | 6.86% | 1.93% | N/A | N/A | N/A | N/A |
| Loan Amount | $37,102 | $34,270 | $124,787 | N/A | N/A | N/A | N/A |
| Maturity (years) | 5.42 | 5.16 | 2.03 | N/A | N/A | N/A | N/A |
| Term Loan (vs. Credit-Line) | 14% | | 34% | 23.33% | | 40.36% | 0.0000 |
| Collateral | 51% | | 32% | 35.92% | | 48.15% | 0.0000 |
| Primary Guarantor | 26.87% | | 34.30% | 10.74% | | 43.37% | 0.0000 |
| SBA Guarantee | 0.80% | | 2.37% | 5.64% | | 22.53% | 0.0000 |
| Internal Credit Score | 1040.85 | 1022.32 | 80.70 | 804.46 | 822.01 | 68.97 | 0.0000 |
| Public (XSBI) Credit Score | 729.96 | 717.40 | 47.95 | 717.99 | 702.93 | 60.48 | 0.0000 |
| Private-Information Residual | 0.0289 | 0.0180 | 0.4764 | -0.0183 | -0.0098 | 0.5813 | 0.0002 |
| Scope of Banking Relationship | 22.12% | | 30.33% | 18.42% | | 37.83% | 0.0000 |
| Months on Books | 38.53 | 30.35 | 54.04 | 20.94 | 18.77 | 45.01 | 0.0000 |
| Monthly Deposit Account Balance | $13,902 | $12,075 | $15,499 | $11,925 | $9,939 | $16,318 | 0.0000 |
| Months in Business | 73.57 | 60.22 | 43.57 | 57.93 | 50.30 | 39.87 | 0.0000 |
| Firm's Monthly Net Income | $80,948 | $75,409 | $102,184 | $54,033 | $47,538 | $61,859 | 0.0000 |
| Firm-Bank Distance (miles by car) | 82.40 | 31.18 | 82.45 | 98.32 | 32.49 | 79.76 | 0.0000 |
| Firm-Comp Distance (miles by car) | 0.95 | 0.51 | 1.25 | 0.86 | 0.56 | 1.12 | 0.0010 |
| Maturity-Matched UST Yield | 4.12% | 3.74% | 2.35% | N/A | N/A | N/A | N/A |
| 5Y - 3M UST Yield Spread (bpts) | 202.40 | 196.32 | 55.87 | N/A | N/A | N/A | N/A |
| Number of Observations | | 3,135 | | | 4,810 | | 7,945 |

**Panel B: In-Person Loan Applications**

| **Loan-Application Outcome** | **Accept** | | | **Reject** | | | ***t*-Test** |
|---|---|---|---|---|---|---|---|
| Variable | Mean | Median | Std Dev | Mean | Median | Std Dev | *P*-val |
| Loan Rate (APR: all-in cost of loan) | 8.46% | 8.13% | 2.72% | N/A | N/A | N/A | N/A |
| Loan Amount | $46,648 | $39,881 | $42,479 | N/A | N/A | N/A | N/A |
| Maturity (years) | 6.71 | 6.19 | 5.38 | N/A | N/A | N/A | N/A |
| Term Loan (vs. Credit-Line) | 22.49% | | 46.72% | 33.79% | | 47.11% | 0.0000 |
| Collateral | 60.12% | | 48.23% | 49.98% | | 48.60% | 0.0000 |
| Primary Guarantor | 34.14% | | 46.80% | 39.23% | | 48.48% | 0.0000 |
| SBA Guarantee | 0.56% | | 4.68% | 12.32% | | 27.23% | 0.0000 |
| Internal Credit Score | 1039.64 | 1045.41 | 138.47 | 817.65 | 855.09 | 128.33 | 0.0000 |
| Public (XSBI) Credit Score | 716.89 | 709.96 | 57.62 | 715.19 | 698.66 | 57.67 | 0.0173 |
| Private-Information Residual | 0.0379 | 0.0112 | 0.7157 | -0.0350 | -0.0106 | 0.5806 | 0.0000 |
| Scope of Banking Relationship | 35.37% | | 43.87% | 25.55% | | 43.32% | 0.0000 |
| Months on Books | 43.26 | 30.65 | 56.28 | 17.69 | 14.50 | 29.60 | 0.0000 |
| Monthly Deposit Account Balance | $17,127 | $11,845 | $62,579 | $11,652 | $10,108 | $20,964 | 0.0000 |
| Months in Business | 116.30 | 96.86 | 107.20 | 91.79 | 81.80 | 98.83 | 0.0000 |
| Firm's Monthly Net Income | $110,525 | $95,203 | $255,740 | $92,210 | $85,187 | $373,508 | 0.0000 |
| Firm-Bank Distance (miles by car) | 9.97 | 2.64 | 21.42 | 10.68 | 2.99 | 28.68 | 0.0228 |
| Firm-Comp Distance (miles by car) | 1.11 | 0.55 | 1.59 | 0.94 | 0.48 | 1.46 | 0.0000 |
| Maturity-Matched UST Yield | 3.93% | 3.86% | 1.94% | N/A | N/A | N/A | N/A |
| 5Y - 3M UST Yield Spread (bpts) | 220.78 | 210.80 | 57.11 | N/A | N/A | N/A | N/A |
| Number of Observations | | 13,102 | | | 12,808 | | 25,910 |

This table reports descriptive statistics for the key variables described in Section 3 in terms of the lending channel (7,945 online applications in Panel A and 25,910 in-person ones in Panel B) and the bank's decision to offer or to deny credit. The last column indicates the $P$-values of a two-sided $t$-test for the equality of the variables' mean conditional on the bank's decision (wherever appropriate). For summary statistics of the control variables by lending channel see Table 1.

Table 4: **The Credit Decision by Loan Type**

| **Specification** | | **1** | | | | | | | **2** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Loan Type | eLoans | | | In-Person Loans | | | eLoans | | | In-Person Loans | | | |
| Variable | Coeff | $P$-val | Marg | Coeff | $P$-val | Marg | Coeff | $P$-val | Marg | Coeff | $P$-val | Marg | |
| Constant | | | | -2.0817 | 0.0001 | | | | | -2.1270 | 0.0001 | | |
| eLoan ($1_{eloan}=1$) | -1.6314 | 0.0001 | -9.33% | | | | -1.6037 | 0.0001 | -11.19% | | | | |
| ln(1+XSBI) | 0.4259 | 0.0001 | 19.99% | 0.2556 | 0.1460 | 0.25% | 0.4019 | 0.0001 | 18.63% | 0.2629 | 0.0397 | 3.43% | |
| ln(1+Internal Score) | 0.1419 | 0.0046 | 2.63% | 0.1683 | 0.0001 | 11.40% | | | | | | | |
| Private-Info. Res. | | | | | | | 0.1928 | 0.0425 | 1.03% | 0.6425 | 0.0001 | 15.79% | |
| Scope | 0.2714 | 0.2228 | 0.27% | 0.9190 | 0.0001 | 2.53% | 0.2560 | 0.3032 | 0.33% | 0.8737 | 0.0001 | 2.29% | |
| ln(1+M. on Books) | 0.3797 | 0.7968 | 0.12% | 0.9313 | 0.0001 | 1.65% | 0.3559 | 0.7968 | 0.12% | 0.8594 | 0.0001 | 1.79% | |
| Scope·PIR | | | | | | | 0.0636 | 0.4529 | 0.42% | 0.1488 | 0.0657 | 1.72% | |
| ln(1+MOB)·PIR | | | | | | | 0.3019 | 0.3960 | 0.24% | 0.0415 | 0.0001 | 1.63% | |
| ln(1+M. in Business) | 0.9189 | 0.0001 | 0.67% | 0.3772 | 0.0001 | 2.71% | 0.8907 | 0.0001 | 0.67% | 0.3630 | 0.0001 | 2.74% | |
| ln(1+Net Income) | 0.6910 | 0.0001 | 1.38% | 0.8964 | 0.0001 | 1.17% | 0.6577 | 0.0001 | 1.67% | 0.8767 | 0.0001 | 1.00% | |
| ln(1+CSHPI) | 0.0884 | 0.1314 | 0.23% | 1.0297 | 0.0390 | 0.52% | 0.0908 | 0.0900 | 0.23% | 0.9659 | 0.0145 | 0.18% | |
| ln(1+F-B Dist) | -0.4299 | 0.8420 | -0.02% | -0.8729 | 0.0515 | -1.15% | -0.4238 | 0.8220 | -0.02% | -0.8956 | 0.0440 | -0.99% | |
| ln(1+F-C Dist) | 0.0894 | 0.4177 | 0.02% | 0.6474 | 0.6820 | 0.22% | 0.0899 | 0.3832 | 0.02% | 0.6012 | 0.6380 | 0.23% | |
| Collateral | 0.5451 | 0.0001 | 2.40% | 0.6006 | 0.0001 | 2.01% | 0.5473 | 0.0001 | 2.81% | 0.5879 | 0.0001 | 1.87% | |
| Primary Guarantor | 0.0510 | 0.0147 | 0.19% | 0.6481 | 0.0001 | 4.12% | 0.0513 | 0.0133 | 0.25% | 0.5646 | 0.0001 | 4.02% | |
| SBA Guarantee | -0.3711 | 0.9280 | -0.34% | -0.1260 | 0.4330 | -0.41% | -0.3419 | 0.9148 | -0.36% | -0.1197 | 0.5343 | -0.32% | |
| Term Loan | -0.0263 | 0.0791 | -0.07% | -0.5006 | 0.0001 | -0.66% | -0.0263 | 0.0839 | -0.07% | -0.4655 | 0.0001 | -0.64% | |
| ln(1+# Branches) | -1.2680 | 0.0001 | -1.14% | -0.5528 | 0.0342 | -1.60% | -1.2836 | 0.0001 | -1.21% | -0.4720 | 0.0390 | -1.77% | |
| ln(1+# Competitors) | -1.0295 | 0.0001 | -1.07% | -0.0701 | 0.0085 | -2.11% | -1.0031 | 0.0001 | -1.18% | -0.0640 | 0.0073 | -1.96% | |
| 4 Quarterly Dum. | | Yes | | | Yes | | | Yes | | | Yes | | |
| 8 State Dummies | | Yes | | | Yes | | | Yes | | | Yes | | |
| 38 SIC Dummies | | Yes | | | Yes | | | Yes | | | Yes | | |
| Number of Obs | | | 33,855 | | | | | | | 33,855 | | | |
| Pseudo $R^2$ | | | 12.06% | | | | | | | 12.04% | | | |

This table reports the results from estimating a logistic discrete-choice model of the bank's credit decision by loan type for our full sample (33,855 observations) using maximum likelihood. We estimate the specification $\Pr\{Y_i = 1\,|\mathbf{x}_i\} = \Lambda(\mathbf{x}_i'\boldsymbol{\beta}+1_{eloan}\cdot\mathbf{x}_i'\boldsymbol{\gamma})$, where $1_{eloan}=1$ for online applications and 0 otherwise and $\Lambda$ is the logistic distribution function, with branch fixed effects and compute clustered standard errors that are adjusted for heteroskedasticity across branch offices and correlation within. The dependent variable is the bank's decision to offer ($Y=1$: 3,135 and 13,102 observations for online and in-person loans, respectively) or to deny ($Y=0$: 4,810 and 12,808 observations for online and in-person loans, respectively) credit. The explanatory variables are our proxies for public, proprietary, and private information, bank-borrower relationship characteristics, firm attributes, measures of the local credit market's competitiveness and various control variables. See Section 3 for a description of the variables and the notes to Table 2 for further methodological details.

Table 5: **Determinants of the Offered Loan Rate**

| **Specification** | **1** | | | | **2** | | | | **3** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Loan Type | eLoans | | In-Person Loans | | eLoans | | In-Person Loans | | eLoans | | In-Person Loans | |
| Variable | Coeff | $P$-val | Coeff | $P$-val | Coeff | $P$-val | Coeff | $P$-val | Coeff | $P$-val | Coeff | $P$-val |
| Constant | | | 7.8736 | 0.0001 | | | 7.4440 | 0.0001 | | | 7.7973 | 0.0001 |
| eLoan ($1_{eloan} = 1$) | -1.3454 | 0.0001 | | | -1.2883 | 0.0001 | | | -1.3791 | 0.0001 | | |
| ln(1+XSBI) | | | | | -1.2408 | 0.0001 | -0.6463 | 0.0001 | -1.2904 | 0.0001 | -0.6844 | 0.0001 |
| ln(1+Internal Score) | | | | | -0.2695 | 0.0001 | -1.6531 | 0.0001 | | | | |
| Private-Info. Res. | | | | | | | | | -0.1488 | 0.2720 | -0.4764 | 0.0001 |
| Scope | -0.4919 | 0.0001 | -0.3281 | 0.0001 | -0.4614 | 0.0001 | -0.2988 | 0.0001 | -0.4309 | 0.0012 | -0.3091 | 0.0001 |
| ln(1+M. on Books) | -0.7862 | 0.0457 | -0.3787 | 0.0001 | -0.7186 | 0.0466 | -0.3573 | 0.0001 | -0.7367 | 0.0330 | -0.3807 | 0.0001 |
| Scope·PIR | | | | | | | | | -0.0311 | 0.7882 | -0.1985 | 0.0001 |
| ln(1+MOB)·PIR | | | | | | | | | -0.0522 | 0.7008 | -0.1289 | 0.0188 |
| ln(1+M. in Business) | -0.9037 | 0.0877 | -0.1458 | 0.2950 | -0.8338 | 0.1816 | -0.1374 | 0.3741 | -0.8329 | 0.0560 | -0.1455 | 0.3932 |
| ln(1+Net Income) | -0.3180 | 0.2907 | -0.7772 | 0.0001 | -0.3075 | 0.3167 | -0.7621 | 0.0001 | -0.2994 | 0.3842 | -0.7600 | 0.0001 |
| ln(1+CSHPI) | -0.5259 | 0.0590 | -0.6326 | 0.0001 | -0.5180 | 0.0953 | -0.5737 | 0.0001 | -0.5487 | 0.1345 | -0.5847 | 0.0001 |
| ln(1+F-B Dist) | -1.7713 | 0.0010 | -1.9030 | 0.0012 | -1.1433 | 0.5154 | -1.0574 | 0.4736 | -1.1096 | 0.5960 | -1.0688 | 0.5194 |
| ln(1+F-C Dist) | 0.7113 | 0.0001 | 0.9647 | 0.0052 | 0.1970 | 0.9350 | 0.5463 | 0.2450 | 0.1880 | 0.9161 | 0.6134 | 0.4235 |
| Collateral | -2.3422 | 0.0001 | -2.3782 | 0.0001 | -2.3203 | 0.0001 | -2.2421 | 0.0001 | -2.4330 | 0.0001 | -2.1043 | 0.0001 |
| Primary Guarantor | -0.8130 | 0.0290 | -0.2991 | 0.0009 | -0.7462 | 0.0459 | -0.2815 | 0.0012 | -0.7275 | 0.0248 | -0.2788 | 0.0002 |
| SBA Guarantee | 0.4457 | 0.3134 | 0.3260 | 0.0247 | 0.4257 | 0.3878 | 0.3057 | 0.0260 | 0.4032 | 0.3830 | 0.3231 | 0.0283 |
| Term Loan | 1.3000 | 0.0370 | 0.3586 | 0.0001 | 1.2480 | 0.0408 | 0.3508 | 0.0001 | 1.2241 | 0.0493 | 0.3171 | 0.0001 |
| ln(1+Maturity) | -0.3996 | 0.0001 | -0.7342 | 0.0001 | -0.3752 | 0.0001 | -0.6924 | 0.0001 | -0.3019 | 0.0001 | -0.5951 | 0.0001 |
| ln(1+# Branches) | -0.1847 | 0.8730 | -0.0534 | 0.7580 | -0.1752 | 0.8977 | -0.0515 | 0.8930 | -0.1701 | 0.8911 | -0.0544 | 0.9015 |
| ln(1+# Competitors) | -0.3311 | 0.9314 | -0.3531 | 0.3885 | -0.3197 | 0.8997 | -0.3244 | 0.5000 | -0.2989 | 0.9616 | -0.3113 | 0.4671 |
| UST Yield | 0.2622 | 0.0001 | 0.2925 | 0.0001 | 0.2472 | 0.0001 | 0.2723 | 0.0001 | 0.2691 | 0.0001 | 0.3016 | 0.0001 |
| Term Spread | 0.2788 | 0.0001 | 0.4356 | 0.0041 | 0.2739 | 0.0001 | 0.4184 | 0.0081 | 0.2704 | 0.0001 | 0.4516 | 0.0003 |
| Lambda | 0.6642 | 0.0463 | -0.3814 | 0.0062 | 0.5893 | 0.2420 | -0.2920 | 0.4678 | 0.5861 | 0.2489 | -0.2960 | 0.4689 |
| 4 Quarterly Dum. | Yes | | Yes | | | Yes | Yes | | Yes | | Yes | |
| 8 State Dummies | Yes | | Yes | | | Yes | Yes | | Yes | | Yes | |
| 38 SIC Dummies | Yes | | Yes | | | Yes | Yes | | Yes | | Yes | |
| Number of Obs | 16,237 | | | | 16,237 | | | | 16,237 | | | |
| Adjusted $R^2$ | 14.06% | | | | 17.28% | | | | 17.15% | | | |

This table reports the results from estimating linear models of the offered loan rate (APR: all-in cost of the loan) of the form $r_i = \mathbf{x}_i'\boldsymbol{\beta} + 1_{eloan} \cdot \mathbf{x}_i'\boldsymbol{\gamma} + \varepsilon_i$, where $1_{eloan} = 1$ for online applications and 0 otherwise, by OLS with branch fixed effects and clustered standard errors that are adjusted for heteroskedasticity across branch offices and correlation within. The explanatory variables are our proxies for public, proprietary, and private information, bank-borrower relationship characteristics, firm attributes, and various control variables. Lambda is the inverse Mills ratio (hazard rate) for the logistic distribution required by the Heckman procedure for sample-selection bias. See Section 3 for a description of the variables.

Table 6: **Descriptive Statistics for Accepted and Declined Credit Offers**

**Panel A: Online (Transactional) Loan Offers**

| **Loan-Offer Decision** | **Accept** | | | **Decline** | | | ***t*-Test** |
|---|---|---|---|---|---|---|---|
| Variable | Mean | Median | Std Dev | Mean | Median | Std Dev | *P*-val |
| Loan Rate (APR: all-in cost of loan) | 6.81% | 6.63% | 1.85% | 7.65% | 8.16% | 2.58% | 0.0000 |
| Loan Amount | $37,789 | $34,987 | $124,485 | $32,833 | $32,737 | $138,135 | 0.4546 |
| Maturity (years) | 5.34 | 5.20 | 2.02 | 5.87 | 5.36 | 2.51 | 0.0000 |
| Term Loan (vs. Credit-Line) | 14% | | 33% | 13% | | 41% | 0.6450 |
| Collateral | 54% | | 31% | 34% | | 39% | 0.0000 |
| Primary Guarantor | 28.55% | | 33.88% | 18% | | 42% | 0.0000 |
| SBA Guarantee | 0.76% | | 2.33% | 1.08% | | 2.85% | 0.0115 |
| Internal Credit Score | 1062.51 | 1027.93 | 79.75 | 987.04 | 1070.79 | 97.66 | 0.0000 |
| Public (XSBI) Credit Score | 728.31 | 716.08 | 45.24 | 734.82 | 726.94 | 49.24 | 0.0067 |
| Private-Information Residual | 0.03 | 0.02 | 0.46 | 0.03 | 0.02 | 0.56 | 0.8598 |
| Scope of Banking Relationship | 23.29% | | 30.03% | 16% | | 36% | 0.0000 |
| Months on Books | 37.88 | 30.79 | 53.57 | 44.59 | 30.62 | 65.75 | 0.0208 |
| Monthly Deposit Account Balance | $14,050 | $12,056 | $15,067 | $14,071 | $12,756 | $18,660 | 0.9797 |
| Months in Business | 76.15 | 60.66 | 43.27 | 56.60 | 60.43 | 53.23 | 0.0000 |
| Firm's Monthly Net Income | $81,123 | $75,927 | $101,117 | $85,128 | $75,440 | $124,760 | 0.4652 |
| Firm-Bank Distance (miles by car) | 84.22 | 31.31 | 81.20 | 75.50 | 31.86 | 100.00 | 0.0476 |
| Firm-Comp Distance (miles by car) | 0.97 | 0.51 | 1.21 | 0.88 | 0.53 | 1.52 | 0.1743 |
| Maturity-Matched UST Yield | 4.33% | 3.67% | 2.31% | 2.94% | 4.28 | 2.87% | 0.0000 |
| 5Y - 3M UST Yield Spread (bpts) | 207.35 | 196.46 | 55.14 | 184.49 | 216.48 | 66.99 | 0.0000 |
| Number of Observations | | 2,715 | | | 420 | | 3,135 |

**Panel B: In-Person (Relationship) Loan Offers**

| **Loan-Offer Decision** | **Accept** | | | **Decline** | | | ***t*-Test** |
|---|---|---|---|---|---|---|---|
| Variable | Mean | Median | Std Dev | Mean | Median | Std Dev | *P*-val |
| Loan Rate (APR: all-in cost of loan) | 8.58% | 8.16% | 2.59% | 8.52% | 8.28% | 2.76% | 0.5266 |
| Loan Amount | $46,833 | $39,970 | $42,806 | $49,300 | $41,089 | $57,307 | 0.1017 |
| Maturity (years) | 6.25 | 6.15 | 5.41 | 6.46 | 6.29 | 5.36 | 0.2462 |
| Term Loan (vs. Credit-Line) | 21.97% | | 47.48% | 29.66% | | 37.45% | 0.0000 |
| Collateral | 62.07% | | 48.51% | 60.97% | | 45.84% | 0.5093 |
| Primary Guarantor | 35.45% | | 47.68% | 33.21% | | 45.35% | 0.1689 |
| SBA Guarantee | 0.52% | | 4.56% | 1.39% | | 3.46% | 0.0000 |
| Internal Credit Score | 1046.79 | 1046.92 | 141.72 | 1047.86 | 1066.65 | 85.15 | 0.8216 |
| Public (XSBI) Credit Score | 715.94 | 708.63 | 54.03 | 719.03 | 713.03 | 58.94 | 0.0968 |
| Private-Information Residual | 0.04 | 0.01 | 0.68 | 0.04 | 0.01 | 0.75 | 0.8812 |
| Scope of Banking Relationship | 35.66% | | 43.67% | 35.29% | | 41.79% | 0.8023 |
| Months on Books | 43.81 | 30.48 | 58.79 | 46.78 | 31.31 | 48.51 | 0.1358 |
| Monthly Deposit Account Balance | $18,013 | $11,954 | $65,413 | $19,238 | $11,942 | $48,615 | 0.5788 |
| Months in Business | 118.47 | 97.83 | 111.38 | 103.14 | 97.91 | 93.35 | 0.0000 |
| Firm's Monthly Net Income | $114,131 | $94,861 | $271,336 | $114,889 | $96,580 | $175,969 | 0.9337 |
| Firm-Bank Distance (miles by car) | 10.11 | 2.64 | 21.87 | 10.02 | 2.17 | 23.75 | 0.9107 |
| Firm-Comp Distance (miles by car) | 1.12 | 0.55 | 1.62 | 1.12 | 0.39 | 1.72 | 0.9879 |
| Maturity-Matched UST Yield | 3.39% | 3.37% | 1.16% | 3.87% | 3.70% | 1.04% | 0.0000 |
| 5Y - 3M UST Yield Spread (bpts) | 216.19 | 208.40 | 55.65 | 240.21 | 211.66 | 61.23 | 0.0000 |
| Number of Observations | | 12,187 | | | 915 | | 13,102 |

This table provides summary statistics for key variables described in Section 3 as a function of the *borrower's* decision to accept (online and in-person applications: 2,715 and 12,187 observations, respectively) or to decline (420 and 915 observations, respectively) the bank's loan offer by lending channel. The last column indicates the *P*-values of a two-sided *t*-test for the equality of the variables' mean conditional on the applicant's decision.

Table 7: **The Decision to Decline a Loan Offer**

| **Specification** | | | **1** | | | | | | **2** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Loan Type | eLoans | | | In-Person Loans | | | eLoans | | | In-Person Loans | | |
| Variable | Coeff | *P*-val | Marg | Coeff | *P*-val | Marg | Coeff | *P*-val | Marg | Coeff | *P*-val | Marg |
| Constant | | | | -4.4031 | 0.0001 | | | | | -4.8724 | 0.0001 | |
| eLoan ($1_{eloan} = 1$) | 1.0927 | 0.0001 | 4.88% | | | | 1.1135 | 0.0001 | 4.28% | | | |
| ln(1+XSBI) | 1.6612 | 0.0001 | 22.89% | 0.7772 | 0.0001 | 25.52% | 1.6532 | 0.0001 | 27.10% | 0.7697 | 0.0001 | 30.35% |
| ln(1+Internal Score) | 0.2839 | 0.0001 | 2.75% | 0.5800 | 0.0001 | 8.72% | | | | | | |
| Private-Info. Res. | | | | | | | 0.3753 | 0.0200 | 3.65% | 0.5379 | 0.0001 | 10.70% |
| Scope | -2.5589 | 0.0001 | -4.96% | -1.0172 | 0.0242 | -3.98% | -2.4749 | 0.0001 | -4.91% | -1.0038 | 0.0390 | -3.20% |
| ln(1+M. on Books) | -1.5607 | 0.0001 | -3.52% | -1.8461 | 0.0001 | -4.17% | -1.6741 | 0.0001 | -3.69% | -1.7965 | 0.0001 | -4.09% |
| Scope·PIR | | | | | | | 0.1303 | 0.6991 | 0.44% | 0.6093 | 0.0001 | 3.63% |
| ln(1+MOB)·PIR | | | | | | | 0.0627 | 0.9680 | 0.23% | 0.7223 | 0.0001 | 3.32% |
| ln(1+M. in Business) | -0.2590 | 0.3837 | -0.30% | -0.3124 | 0.0207 | -0.20% | -0.2741 | 0.3005 | -0.34% | -0.3325 | 0.0289 | -0.22% |
| ln(1+Net Income) | 2.3368 | 0.0001 | 1.72% | 1.9730 | 0.0001 | 2.48% | 2.3335 | 0.0001 | 2.62% | 1.9760 | 0.0001 | 2.43% |
| ln(1+CSHPI) | 0.9326 | 0.0088 | 0.66% | 0.0262 | 0.95 | 0.31% | 1.0016 | 0.0004 | 0.65% | 0.0276 | 0.9315 | 0.34% |
| ln(1+F-B Dist) | 2.1461 | 0.0001 | 1.82% | 2.0528 | 0.0001 | 0.97% | 2.0690 | 0.0001 | 1.66% | 2.0314 | 0.0001 | 0.85% |
| ln(1+F-C Dist) | -1.0768 | 0.0001 | -0.31% | -1.0918 | 0.0001 | -0.27% | -1.0525 | 0.0001 | -0.35% | -1.0580 | 0.0001 | -0.25% |
| Collateral | 0.0422 | 0.9850 | 0.15% | 0.1780 | 0.5530 | 0.20% | 0.0431 | 0.9240 | 0.15% | 0.1812 | 0.7690 | 0.28% |
| Primary Guarantor | 2.0609 | 0.0001 | 3.92% | 2.1411 | 0.0001 | 4.94% | 2.0262 | 0.0001 | 4.00% | 2.2082 | 0.0001 | 4.98% |
| SBA Guarantee | 1.2450 | 0.0001 | 0.03% | 0.2710 | 0.0248 | 0.11% | 1.2261 | 0.0001 | 0.08% | 0.2630 | 0.0289 | 0.11% |
| Term Loan | -0.7127 | 0.0001 | -0.38% | -0.0122 | 0.9890 | -0.03% | -0.6795 | 0.0001 | -0.34% | -0.0116 | 0.9276 | -0.07% |
| APR | 0.2651 | 0.0001 | 9.48% | 0.3955 | 0.0001 | 12.82% | 0.2587 | 0.0001 | 9.62% | 0.3752 | 0.0001 | 11.80% |
| ln(1+Loan Amount) | -2.0620 | 0.0001 | -4.12% | -2.0135 | 0.0001 | -2.27% | -2.1222 | 0.0001 | -4.59% | -1.9767 | 0.0001 | -2.63% |
| ln(1+Maturity) | -0.1770 | 0.0001 | -0.95% | -0.2959 | 0.0001 | -1.37% | -0.1793 | 0.0001 | -1.01% | -0.2752 | 0.0001 | -1.66% |
| ln(1+# Branches) | 0.4441 | 0.4853 | 0.16% | 0.4857 | 0.0440 | 0.35% | 0.4024 | 0.7751 | 0.17% | 0.4835 | 0.0204 | 0.34% |
| ln(1+# Competitors) | 0.6081 | 0.0222 | 0.29% | 0.0237 | 0.9307 | 0.13% | 0.6429 | 0.0229 | 0.27% | 0.0251 | 0.9586 | 0.18% |
| UST Yield | 0.8489 | 0.0001 | 2.36% | 1.1566 | 0.0001 | 3.50% | 0.8587 | 0.0001 | 2.69% | 1.1876 | 0.0001 | 3.80% |
| Term Spread | -1.0548 | 0.0290 | -1.70% | -1.0086 | 0.0001 | -2.65% | -1.0109 | 0.0479 | -1.66% | -0.9967 | 0.0001 | -2.78% |
| 4 Quarterly Dum. | | Yes | | | Yes | | | Yes | | | Yes | |
| 8 State Dummies | | Yes | | | Yes | | | Yes | | | Yes | |
| 38 SIC Dummies | | Yes | | | Yes | | | Yes | | | Yes | |
| Number of Obs | | | 16,237 | | | | | | 16,237 | | | |
| Pseudo $R^2$ | | | 6.72% | | | | | | 6.83% | | | |

This table reports the results from estimating a logistic discrete-choice model of the borrower's decision to refuse the bank's loan offer and to seek credit elsewhere by full-information maximum likelihood for the subsample of successful loan applications (15,897 observations). As before, we use branch fixed effects and clustered standard errors that are adjusted for heteroskedasticity across branch offices and correlation within. The dependent variable is the applicant's decision to decline ($Y = 1$: 420 online and 915 in-person observations) or to accept ($Y = 0$: 2,715 online and 12,187 in-person observations) the bank's offer; the explanatory variables are our usual proxies for public, proprietary, and private information, bank-borrower relationship characteristics, firm attributes, and various control variables. See Section 3 for a description of the variables and the notes to Table 2 for further details.

Table 8: **The Likelihood of Credit Delinquency**

| **Specification** | **1** | | | | | | **2** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Loan Type | eLoans | | | In-Person Loans | | | eLoans | | | In-Person Loans | | |
| Variable | Coeff | $P$-val | Marg | Coeff | $P$-val | Marg | Coeff | $P$-val | Marg | Coeff | $P$-val | Marg |
| Constant | | | | -1.1865 | 0.0001 | | | | | -1.1872 | 0.0001 | |
| eLoan ($1_{eloan} = 1$) | 1.1476 | 0.0001 | 2.72% | | | | 1.1523 | 0.0001 | 2.95% | | | |
| ln(1+XSBI) | -1.8501 | 0.0001 | -19.97% | -0.9446 | 0.0001 | -21.35% | -1.7680 | 0.0001 | -22.79% | -0.9028 | 0.0001 | -20.31% |
| ln(1+Internal Score) | -0.2720 | 0.0001 | -4.49% | -0.4469 | 0.0001 | -9.82% | | | | | | |
| Private-Info. Res. | | | | | | | -0.2656 | 0.0001 | -4.12% | -0.1027 | 0.0001 | -12.88% |
| Scope | -0.4961 | 0.0001 | -1.06% | -0.7620 | 0.0001 | -2.78% | -0.5133 | 0.0001 | -1.20% | -0.7598 | 0.0001 | -2.94% |
| ln(1+M. on Books) | -0.9643 | 0.0289 | -0.96% | -0.3010 | 0.0001 | -3.50% | -1.0539 | 0.0001 | -0.91% | -0.3225 | 0.0001 | -3.18% |
| Scope·PIR | | | | | | | -0.5721 | 0.0001 | -1.84% | -0.3474 | 0.0001 | -3.38% |
| ln(1+MOB)·PIR | | | | | | | -0.4899 | 0.3507 | -0.32% | -0.2096 | 0.0140 | -1.62% |
| ln(1+M. in Business) | -0.8820 | 0.0582 | -2.87% | -0.0165 | 0.8617 | -3.24% | -0.8561 | 0.0770 | -3.50% | -0.0172 | 0.8720 | -3.83% |
| ln(1+Net Income) | -0.5422 | 0.0001 | -2.18% | -0.0842 | 0.0001 | -1.97% | -0.5806 | 0.0001 | -2.59% | -0.0919 | 0.0001 | -1.83% |
| ln(1+CSHPI) | -0.8409 | 0.0001 | -0.63% | -0.0706 | 0.0001 | -0.49% | -0.9012 | 0.0070 | -0.70% | -0.0736 | 0.0001 | -0.47% |
| ln(1+F-B Dist) | 0.2819 | 0.5480 | 0.11% | 0.2339 | 0.3728 | 0.12% | 0.2674 | 0.6844 | 0.12% | 0.2529 | 0.2015 | 0.19% |
| ln(1+F-C Dist) | -0.7299 | 0.3930 | -0.04% | -0.2175 | 0.5770 | -0.04% | -0.6994 | 0.6510 | -0.04% | -0.2308 | 0.4900 | -0.08% |
| Collateral | -0.5385 | 0.0001 | -1.43% | -0.1912 | 0.0001 | -1.91% | -0.5871 | 0.0001 | -1.82% | -0.1967 | 0.0001 | -2.35% |
| Primary Guarantor | -0.3894 | 0.0001 | -2.80% | -0.5462 | 0.0001 | -1.31% | -0.3952 | 0.0001 | -2.48% | -0.5377 | 0.0001 | -1.63% |
| SBA Guarantee | 2.9317 | 0.0001 | 0.33% | 0.5753 | 0.0001 | 2.95% | 3.0405 | 0.0001 | 0.23% | 0.5554 | 0.0001 | 3.20% |
| Term Loan | 0.2625 | 0.0001 | 0.42% | 0.6510 | 0.0001 | 0.26% | 0.2733 | 0.0001 | 0.59% | 0.6747 | 0.0001 | 0.34% |
| APR | 2.0545 | 0.0001 | 4.99% | 1.1254 | 0.0191 | 7.06% | 1.9412 | 0.0001 | 4.97% | 1.1269 | 0.0121 | 7.02% |
| ln(1+Loan Amount) | -0.9771 | 0.0001 | -8.57% | -1.5777 | 0.0001 | -9.79% | -1.0305 | 0.0001 | -10.88% | -1.5018 | 0.0001 | -9.37% |
| ln(1+Maturity) | -0.4464 | 0.0001 | -1.09% | -0.8171 | 0.0001 | -1.44% | -0.4987 | 0.0001 | -1.29% | -0.8007 | 0.0001 | -1.59% |
| ln(1+# Branches) | 2.7084 | 0.0001 | 0.20% | 0.1071 | 0.0001 | 0.37% | 2.6964 | 0.0001 | 0.25% | 0.1146 | 0.0001 | 0.41% |
| ln(1+# Competitors) | 3.7498 | 0.0001 | 0.51% | 0.1644 | 0.0001 | 0.12% | 3.8523 | 0.0001 | 0.47% | 0.1691 | 0.0001 | 0.15% |
| UST Yield | 0.4750 | 0.2840 | 0.47% | 0.4661 | 0.0001 | 0.71% | 0.4515 | 0.3355 | 0.42% | 0.4427 | 0.0001 | 0.75% |
| Term Spread | 1.1993 | 0.0001 | 1.47% | 1.8662 | 0.0001 | 1.43% | 1.2402 | 0.0001 | 1.71% | 1.8641 | 0.0001 | 1.09% |
| 4 Quarterly Dum. | | Yes | | | Yes | | | Yes | | | Yes | |
| 8 State Dummies | | Yes | | | Yes | | | Yes | | | Yes | |
| 38 SIC Dummies | | Yes | | | Yes | | | Yes | | | Yes | |
| Number of Obs | 14,902 | | | | | | 14,902 | | | | | |
| Pseudo $R^2$ | 12.44% | | | | | | 12.11% | | | | | |

This table reports the results from estimating a logistic model of the likelihood that a loan becomes 60 days overdue within 18 months of origination by full-information maximum likelihood for the subsample of actual loans booked by the bank (14,613 observations). Again, we use branch fixed effects and clustered standard errors that are adjusted for heteroskedasticity across branch offices and correlation within. The dependent variable is the performance status of the loan during its first 18 months: at most 60 days overdue (corresponding to our bank's internal definition of a delinquent loan $Y = 1$: 91 and 319 online and in-person observations, respectively), or current ($Y = 0$: 2,624 and 11,868 online and in-person observations, respectively). The explanatory variables are our proxies for public, proprietary, and private information, bank-borrower relationship characteristics, firm attributes, and various control variables; see Section 3 for a description of the variables and the notes to Table 2 for further details.

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